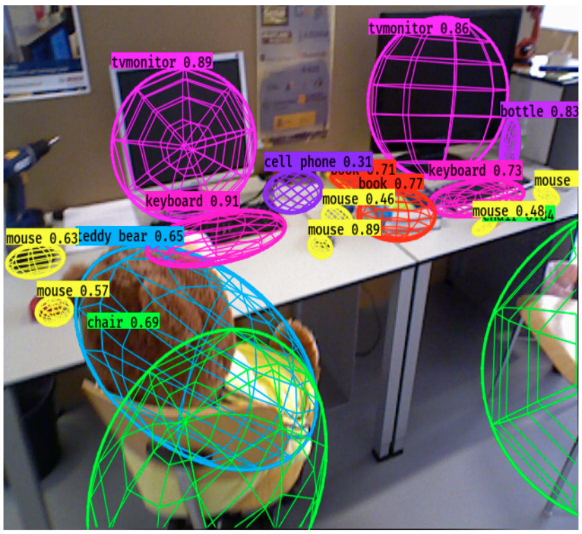
Semantic Mapping

Mid-Term Report

1 Quadric SLAM



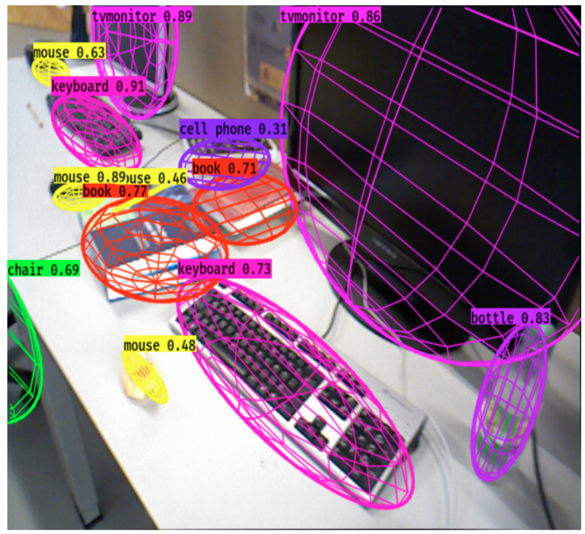


Figure 1: **QuadricSLAM**: Ellipsoids fitted on objects in image plane[1]

- The Quadric SLAM is a semantic SLAM approach where each object within the environment is represented using dual quadrics whose parameters are estimated and optimised using multi-view geometry.
- The optimisation is based on the 2D bounding box generated for each object observed at different view points. This object detection method also helps to add semantic label to each object.
- SLAM involves performing mapping and robot pose estimation in a combined fashion. Here the robot camera poses and the quadric parameters are estimated using underlying factor graph based back-end. The odometry errors in the factor graph could be reduced through the loop closure which is aided by re-observing the quadric representation of the object at different view points. Thus both the odometry and the observation are aiding to minimize the errors of each other.
- In the initial paper released by the authors [2], a monocular perspective camera was used to input RGB images to the front-end of the framework without any depth information.
- The quadric used in this application is ellipsoid because its a closed surface. It can capture the position(3 parameters), radius or size(3 parameters) and orientation(3 parameters) of the object in the 3D world. This kind of representation can help to reduce the memory required to store the dense 3D representation of the surface of the object and at the same time serves all the basic purposes like localization, semantic navigation and planning tasks.
- The following section explains about the mathematics behind dual quadric representation. The section is a summarized version of the content in section 3 of the Quadric SLAM paper[2].

- For each view of an object, a 2D bounding box is generated with 4 corners x_1, x_2, x_3 and x_4. Each one can be represented using a 3D homogeneous vector.

- Further, the 4 edges of the bounding box l_1, l_2, l_3 and l_4 can be represented as a cross product of these corner points. $l_1 = x_1 X x_2, l_2 = x_2 X x_3, l_3 = x_3 X x_4$ and $l_4 = x_4 X x_1$.

- The lines drawn from the camera center to each of the four corner points can back-project the four edge lines into four 3D planes. The equation of the 3D plane can be written as $\pi_i = P^T l_i$ where i is the index of the 2D edge for which the 3D plane is generated. P is the camera projection matrix, P = K[R t] where K is the intrinsic parameter matrix of size 3x3 and R and t are the extrinsic parameter matrix of the camera of size 3x4. Therefore P is a matrix of size 3x4 and the resultant 3D plane π_i is a 4D homogeneous vector.

- Thus a single view can create a constrained 3D space enveloped by four 3D planes. Since we don't have depth information from a single view, we may need multiple views to further constrain the object shape and orientation.

- The next important concept is what and how to represent a quadric. A quadric Q is a 3D surface that is characterized by a set of points x on the surface that satisfies the equation $x^T Q x = 0$. Q is a 4x4 symmetric matrix.

- The same equation can be rewritten in terms of tangential planes that passes through each of these points that can create an closing envelope around the surface. $\pi^T Q^* \pi = 0$. Q^* is called as dual quadrics or dual representation of the quadric which is calculated by $Q^* = Q^{-1}$ if Q has an inverse or $Q^* = adjoint(Q)$.

- Since Q^* is a symmetric 4x4 matrix, there are 10 unique elements. Three for centroid, three for size or radius, three for orientation and one for scaling factor which is usually kept constant as -1. So only need to optimize for 9 parameters. Q^* can be represented as $Q^* = T Q_0^* T^T$ where Q_0^* is the representation of an ellipsoid centered at origin and T is the homogeneous transformation matrix of size 4x4 involving a rotation and translation parameter [R t] to transform the ellipsoid from origin.

$$Q_0^* = \begin{bmatrix} r_1^2 & 0 & 0 & 0 \\ 0 & r_2^2 & 0 & 0 \\ 0 & 0 & r_3^2 & 0 \\ 0 & 0 & 0 & -1 \end{bmatrix}$$

- The parameters r_1, r_2 and r_3 governs the size or radius of the ellipsoid. The orientation and centroid parameters are incorporated as rotation and translation parameters in the homogeneous transformation matrix T. After matrix multiplication, the matrix Q^* turns into a transformation matrix where the centroid is the last column of Q^* as a homogeneous 4x1 vector. The orientation parameters pitch, yaw, roll has to be extracted from the first 3x3 dimension of the dual quadric matrix.

- The above concept of $\pi_i^T Q^* \pi_i = 0$ represents an 3D equation. However the bounding box observations we obtained from the detectors are in 2D. We have to convert from quadrics to conics which is ellipsoids to ellipses in this case. The dual conics C^* can be written as $C^* = P Q^* P^T$ where the 3D ellipsoid Q^* is projected onto the 2D image plane using the camera projection matrix P mentioned before.

- The definition of quadrics also remains same for conics $x^T C x = 0$ where x is now replaced with 2D points. And as tangential planes exists for points in 3D, tangential lines exists for points in 2D. Hence $\pi^T Q^* \pi = 0$ for quadrics could be replaced by $l^T C^* l = 0$ for conics where C^* is the dual conic representation and l is the set of tangential lines.

- Substituting the expression for dual conics in the above equation yields, $l^T P Q^* P^T l = 0$.

- Per detection of an object from a view point, the bounding box generates 4 lines which can act as 4 constraints on the dual quadrics. For dual quadrics Q^*, there are 9 unknown parameters and atleast 3 observations from different view points are needed to generate a solution for the same.

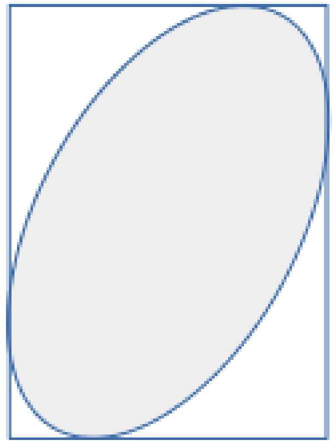


Figure 2: Four tangential lines to the object conic ellipse

- The following section explains about the mathematics behind using the dual quadric representation in SLAM backend for optimization and corrections. The section is a summarized version of the content in section 4 of the Quadric SLAM paper[2].
- To define the factor graph, we define certain parameters for the odometry and observations:
  - A set of robot camera poses X = $\{x_i\}$ where i is the index of the pose at which a particular observation is made.
  - A set of landmarks Q = $\{q_j\}$ where q_j indicates the dual quadric representation for the object j.
  - A set of observations U = $\{u_i\}$ where u_i is the odometry data available via wheel odometry or visual odometry.
  - A set of lines L = $\{l_i jk\}$ where k ranges from 0 to 4. $l_i jk$ denotes the line k of the bounding box for object j being viewed at pose i.
- The conditional probability distribution could be written as:

$$P(X, Q \mid U, L) \propto \underbrace{\prod_i P\left(\mathbf{x}_{i+1} \mid \mathbf{x}_i, \mathbf{u}_i\right)}_{\text{Odometry Factors}} \cdot \underbrace{\prod_{ijk} P\left(\mathbf{q}_j \mid \mathbf{x}_i, \mathbf{l}_{ijk}\right)}_{\text{Landmark Factors}} \tag{1}$$

- This modelled representation of factor graph tries to find the optimal solution for poses X^* and landmarks Q^* for a given set of odometry observations U and detected bounding box lines L. In other words, we are trying to find maximum a posteriori values for X and Q through non-linear optimization strategies.
- The equation involving dual quadric parameter($l^T PQ^* P^T l = 0$) can be optimized through least squares method. $\mathbf{q}_j^* = \operatorname{argmin}_{\mathbf{q}_j} \sum_{ik} \left\| \mathbf{l}_{ijk}^\top \mathbf{P}_i \mathbf{Q}_{(\mathbf{q}_j)}^* \mathbf{P}_i^\top \mathbf{l}_{ijk} \right\|^2$. This maximizes the probability distribution for landmark factors in the above equation (1).
- Further, maximizing the conditional probability distribution (1) could be simplified by minimizing the negative log of the probability. Thereby, the multiplication terms turns to addition and turning the entire SLAM problem into a least squares problem.
- The factor graph is solved using Levenberg-Marquardt optimization strategy for non-least squares problem in this case and GTSAM[3] is the library being used in the backend for efficient computations by taking advantage of sparse nature of the jacobian matrixes.

- If depth information is available, it could also be added to the least squares problem as an extra error term that can represent additional knowledge of the problem which can be added as a factor in the factor graph.

$$X^*, Q^* = \underset{X,Q}{\operatorname{argmin}} \underbrace{\sum_i \left\| \mathbf{e}_i^{\text{odo}} \right\|_{\Sigma_i}^2}_{\text{Odometry Factors}} + \underbrace{\sum_{ijk} \left\| \mathbf{e}_{ijk}^{\text{quadric}} \right\|_{\Lambda_{ijk}}^2}_{\text{Quadric Landmark Factors}} + \underbrace{\sum_{ij} \left\| \mathbf{z}_{ij} - \mathbf{T}_i \left(\mathbf{q}_j^{\text{t}} \right) \right\|_{\Omega_{ij}}^2}_{\text{Relative Position Factors}} \tag{2}$$

- Each of the three factors are trying to minimize the odometry error, dual quadric parameters error and centroid of the quadric (last column of dual quadric) error respectively. In the third term, z_{ij} is the observed depth of the object j at pose i and $T_i(q_j^t)$ is transforming the centroid from last column of dual quadric representation from world coordinate to the robot coordinate at pose i. So the last term is for centroid correction.

- Another task is the variable initialization for robot poses x_i and dual quadrics q_i. x_i is initialized with the help of odometry data available from wheel odometry or visual odometry and q_i is initialized as a identity matrix of size 4x4.

1.1 Orientation Factor

- The same authors later came up with a continuation of this work to incorporate prior knowledge of the world to better orient the quadrics within the environment using orientation constraints[4]. The prior knowledge is that we need to assign each object class to one of the category such as Horizontal, Vertical or Unassigned. This corresponds to what is the normal pose of the object in relation with gravity. For example, a chair can be Vertical and a laptop can be Horizontal.

- Further, the major axis of the quadric is aligned close to z-axis(vertical line) or close to perpendicular to z-axis(horizontal line) based on the prior knowledge of the normal poses of the objects.

- To find the major axis, eigen values are calculated from the dual quadric representation involving only the rotation components and eigen vector corresponding to the largest eigen value is identified. Further, a cosine similarity between this vector and the z-axis is calculated.

- This value should be optimized towards 1(cosine similarity of 1) if the prior knowledge of the object pose is Vertical(gravity, major axis and z-axis in same direction). And the value should be optimized towards 0(cosine similarity of 0) if the prior knowledge of the object pose is Horizontal(major axis is perpendicular to gravity and z-axis).

- To implement this in factor graph, the problem is made into a least squares problem and added as a factor to the factor graph. To the equation (2), a fourth factor is added as orientation factor.

$$\underbrace{\sum_j \left\| g\left(l_j\right) - c_j \right\|_{\sigma_j}^2}_{\text{Orientation Factors}} \tag{3}$$

- c_j is the cosine similarity value being calculated and $g(l_j)$ is the actual expected cosine similarity for the particular label l of the object j which can be 0 for Horizontal and 1 for Vertical.

- One of the problem of this approach is that, we need to assign each known class to one of the category such as Horizontal, Vertical or Unassigned. And, in the example which they have shown, they assigned book to be horizontal which can be a wrong assumption as books kept in shelf are in vertical orientation.

- This approach of adding the fourth orientation factor is not implemented in the available code of Quadric SLAM.

1.2 Sensor Model

- In the final paper released by the same authors in 2019[1], they have added a sensor model to correct the errors in the predicted 2D bounding box of partially observable objects. We need to only consider the conic/ellipse part of the object within the image plane.

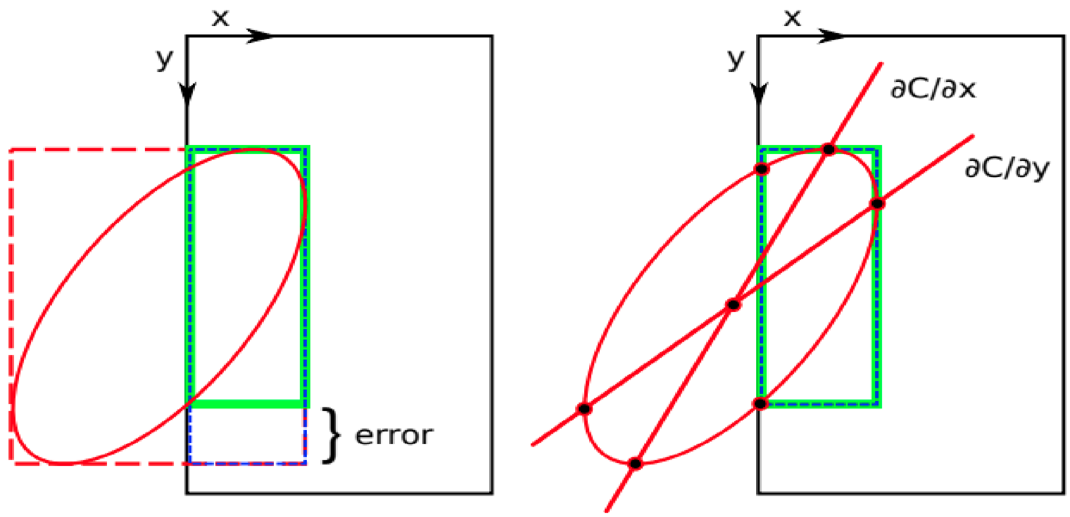


Figure 3: **Left**: The dotted red square is the predicted bounding box by the detector. Green square is the required bounding box. Violet is the error. **Right**: Error is removed through conic extreme x, y parameters[1]

- In the above figure, the black box is the image viewed by the robot and only a part of the conic of the object is visible within the image plane. Normally, the edges of the bounding box is truncated based on the edges of the image plane. And this resulted in the error component depicted by violet color where the object conic is absent.
- To reduce this geometric error, the bounding box within image plane is cropped using the conic extreme x and y parameters. For this, 4 points representing extreme points of the conic are selected along with the points that are intersecting between the conic and the 2D bounding box. All the points that lie outside the image plane are removed and from the remaining points within the image plane, the max and min values of x and y are determined which are used to create the accurate green 2D bounding box.
- The results of the experiments showed that this feature significantly improved the estimated trajectory and the quadric mapping in terms of reduced trajectory and landmark quality errors.
- The previously used error term in Quadric Landmark Factor was an algebraic one. That is, minimizing $\mathbf{q}_j^* = \mathrm{argmin}_{\mathbf{q}_j} \sum_{ik} \left\| \mathbf{l}_{ijk}^\top \mathbf{P}_i \mathbf{Q}_{(\mathbf{q}_j)}^* \mathbf{P}_i^\top \mathbf{l}_{ijk} \right\|^2$. This is replaced by the geometric error proposed by the new sensor model, $\left\| \mathbf{b}_{ij} - \boldsymbol{\beta}_{(x_i,q_j)} \right\|_{\Lambda_{ijk}}^2$. Here, b_{ij} is the bounding box observed for object j at robot pose i. And $\boldsymbol{\beta}_{(x_i,q_j)} = BBOX(C_{ij})$ is the expected geometrically corrected bounding box for the conic C of the object j observed at pose i. $C = adjoint(C^*) = adjoint(P_i Q_j^* P_i^T)$ where P_i is the camera projection matrix at pose i and Q_j^* is the dual quadric representation of the object j.
- The 2D object detector used in the experiments is YOLOv3.

1.3 Variable Initialization

- In the final paper of Quadric SLAM[1], another initialization method for quadrics are proposed. Using the dual quadric representation of quadric $\pi^T Q^* \pi = 0$, we can create a linear set of equation which can be solved using SVD if atleast 3 views for the same object quadric is observed. The last column of decomposed matrix V gives the solution for the equation. The translation parameters can be obtained from the last column and the orientation parameters can be obtained from the first three columns of the solved Q^* matrix. The size is extracted from the eigen values.[1]

1.4 GTSAM

- GTSAM[3] library is used to build the factor graph backend for QuadricSLAM and performs as incremental solvers. The robot pose and the dual quadric matrix are represented as nodes which are the latent variables that needs to be estimated. The pose nodes are constrained by the odometry factors and the pose-quadric nodes are constrained by the bounding box factors.

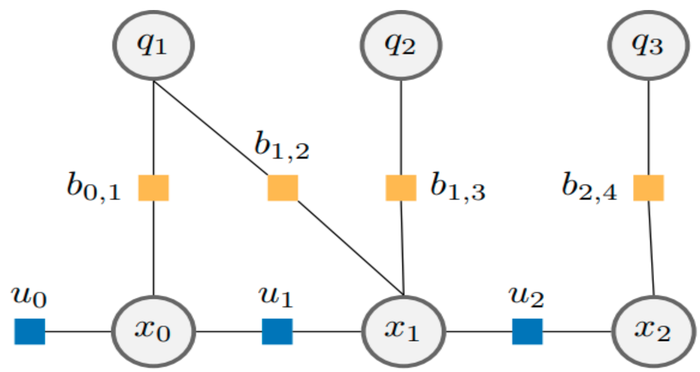


Figure 4: **Factor Graph of QuadricSLAM**: odometry factors in blue, quadrics bbox factors in yellow [4]

- In the above figure, it can be seen that the quadric q_1 is observed from two robot poses x_0 and x_1. As the same object is observed from different poses, it adds better constraint to optimize the quadric parameters. Actions(in this case robot motion) introduces uncertainty whereas the observations (in this case the bounding boxes of detection) helps to reduce the uncertainty in the pose graph.

- Another important constraint in factor graph is loop closure constraint. Using the image or quadric features, when the robot detects that its in a pose which was visited at a previous point in time, it can create a loop closure constraint which can help to reduce the overall error in the factor graph. This is also a field of challenge where we need to verify or make sure that the features are qualified enough for a loop closure to avoid false positive loop closure detection which can have a bigger negative effect on the factor graph.

- The author's of QuadricSLAM, extended the GTSAM functionalities by creating another library called gtsam_quadrics which handles quadrics related functions.

- Some of the important functions used in QuadricSLAM are:
  - gtsam.symbol - used to symbolically represent the robot pose and quadric variables as nodes within the factor graph.
  - gtsam.noiseModel.Diagonal.Sigmas - can be used to define a noise model which is added into the factor graph when an odometry measurement or observation is used to add a constraint between 2 variables or nodes. It indicates with how much uncertainty, we are adding the measurement to the factor graph.
  - gtsam_quadrics.ConstrainedDualQuadric - used to represent the quadric based on the given the input parameters like rotation, translation, radii matrixes as it has different constructors.
  - gtsam.NonlinearFactorGraph - Used to initialize a factor graph onto which the robot pose and quadrics are added as latent variables along with the odometry and bounding box measurements as factors with an assosciated noise model.

– gtsam.Cal3_S2 - to generate calibration matrix
– gtsam.Pose3 - create a 3D pose of rotation and translation matrix based on the input provided.
– gtsam.Rot3 - create a 3D rotational matrix.
– gtsam.PriorFactorPose3 - to generate the initial robot pose with a prior noise model which is added to the factor graph.
– gtsam.BetweenFactorPose3 - to add the odometry measurement factor between two robot poses with a odometry noise model which is added to the factor graph.
– gtsam_quadrics.BoundingBoxFactor - to add the bounding box observation as a factor between a robot pose and a quadric which is added to the factor graph. Bounding box noise is also assosciated with the function.
– gtsam_quadrics.QuadricCamera.project - given a dual quadric matrix and robot pose, it will generate the 2D view(conic) of the quadric in the image plane from which using the function bounds(), we can obtain the 2D bounding box virtually.
– gtsam.LevenbergMarquardtOptimizer - Given the factor graph and a initial estimate for the robot poses and quadric latent variables, a non-linear optimization is applied on the graph to get the results.

- It can be seen that there is a noise attached with every odometry, observation and prior measurement factors.

1.5 Code Explanation

1.5.1 Overall Framework

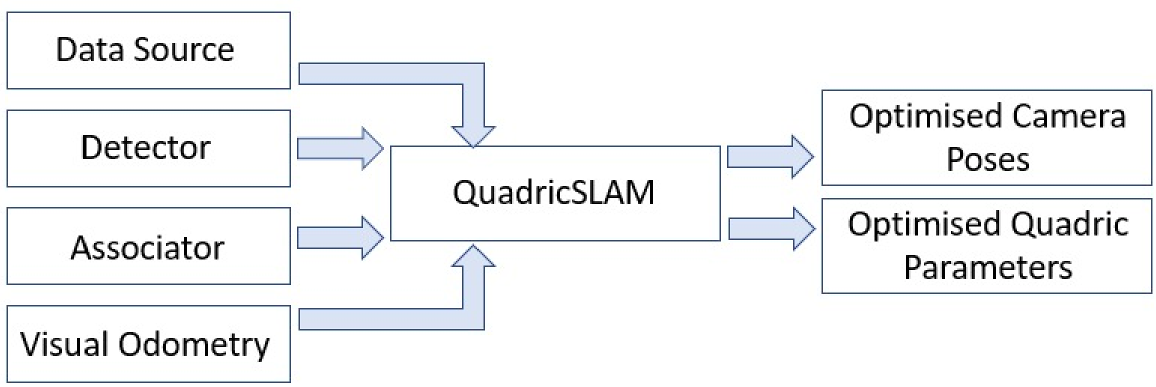


Figure 5: QuadricSLAM framework

- The above figure depicts the general functional framework of QuadricSLAM. QuadricSLAM is implemented as a class which takes in the class objects of data source, detector, associator and visual odometry. And what we get out of QuadricSLAM is the optimised camera poses and quadric parameters which can be used to create the map. Each component is explained below.

1.5.2 Data source

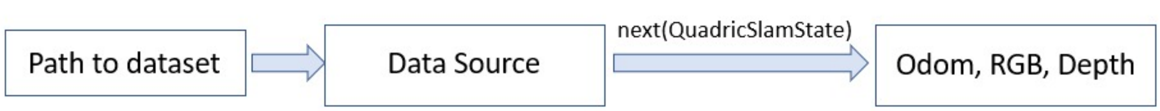


Figure 6: Data source

- Used to either access an available dataset(acts as a dataloader) or provide the live data to the QuadricSLAM algorithm. The data include odometry, RGB image and depth image. These data is retrieved by QuadricSLAM by calling the next() function of data source.
- The odometry should be converted from quaternion or transformation matrix format to SE3() pose representation in spatial math.
- Datasource also maintains an internal counter to step through each data in time and also checks for data read completely or not.
- Depthscaling factor and RGB calibration parameters are also stored here. Images are calibrated before passing into the QuadricSLAM.
- If using a live data, then the configuration of the data source can be defined in the init() function. If using an available dataset, then the path to the dataset is to be passed into here.

1.5.3 Detector

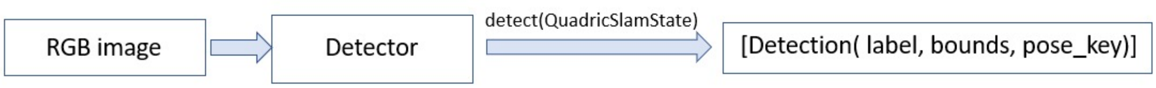


Figure 7: Detector

- Used for detecting objects in each RGB image frame. The detect() function outputs the list with elements of object type Detection which contains label of the object, list of 4 values of the bounding box(x,y of top-left and bottom-right corners) and the pose_key which indicates at which pose number the current detection is made.
- The default detector used here is the detectron2 Faster-RCNN. A pretrained model on certain labels is used here. Only those objects are detected.
- In the experiments which we are going to perform on BOP dataset, we are going to avoid the usage of a detector and instead provide the bounding box directly available from the dataset. This will help us to evaluate the performance of QuadricSLAM given the noise from the bounding box is kept minimum.

1.5.4 Associator

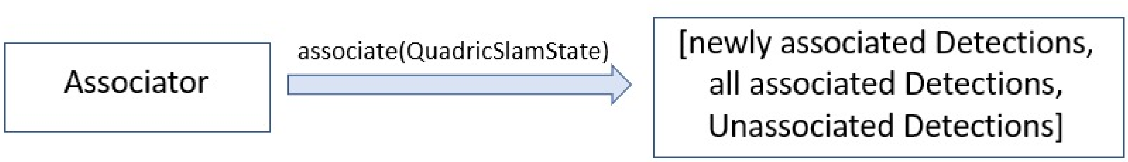


Figure 8: Associator

- Data Associator takes the detections made in the current state and all previously unassosciated detections and used it to compare with previously assosciated detections to decide whether to match the unassosciated detection with a previously assosciated detection(same quadric key to both detection) or to treat the detection as a new object(new quadric key to the detection).
- Basically, it decides whether a detection should be given an existing quadric key or create a new quadric key for it.

- The decision is based on the Intersection Over Union(IOU) value between the detection and an existing quadric. With respect to the current robot pose, all the existing quadrics within the factor graph is projected in 2D plane as a enclosing bounding box. For each current detection bounding box, we are comparing its overlap with each bounding box generated within the map of QuadricSLAM. If the overlap is below a certain threshold, then treated as a new object with a new quadric key. Otherwise, assosciated to an existing object with the quadric key of the overlapping quadric.
- In the init() function, we can specify threshold above which an assosciation should be made.
- The associate() function outputs the list of the newly associated detections(objects for which a new quadric has been created in the current step), updated list of associated detections(all objects that has been assosciated with a quadric key), updated list of unassociated detections(objects that doesn't have a quadric key - usually passed as an empty list).

1.5.5 Visual Odometry

Figure 9: Visual Odometry

- Could be used to generate the odometry from current and previous RGBD image. Usefull when no odometry information is available.
- Here, RgbdOdometry from CV2 library is being used. The current and previous RGB images are converted intro gray scale and provided as input along with their depth images to compute the odometry.
- odom() function returns the odometry value.
- Other visual odometry approaches suggested by the authors are ORB-SLAM2 with loop closure disabled or Kimera VIO(Visual Inertial Odometry) to get a less noisy odometry value.

1.5.6 Main code

- There are two ways to initialize a quadric. initialise_quadric_ray_intersection() and initialise_quadric_from_depth().
- In initialise_quadric_ray_intersection(), the translation and rotation of the poses at which a particular object is seen is used to project rays into 3D space and using least squares method to find the closet converging point which is a good approximation of the quadric centroid. The initial orientation and size of the quadric is random. In the code, the size is set to (1, 1, 0.1).
- In initialise_quadric_from_depth(), the quadric can be initialized from a single view or image. To estimate centroid, the z coordinate is calculated as the mean of the depth of points within the bounding box of detection. x and y coordinate are calculated as a calibrated value representing the centre point of the bounding box. The x,y radii of the quadric is calculated as a calibrated value of the height and width of the bounding box. The z radii is assumed to be a predefined object depth of 0.1. The orientation of the quadric can be estimated using the rotation, translation of the camera pose and the quadric centroid through gtsam.PinholeCameraCal3_S2.Lookat() function.
- There are two modes of optimization. Optimization in a batch or in an incremental way. If its set to true, then the optimization of the unknown variables occur only at the end of processing all the images. If false, then the optimization runs along with each detection step.

- There are 3 noise models used in this application. One for the prior noise which is added along with the initial pose of the robot. Another one for odometry measurement noise which is added to the constraint between two robot pose variables. Third one for bounding box noise which is added for the constraint between a robot pose and the observation measurement which is a bounding box. This noise is due to the instability of bounding box being generated for an object which is evident for small objects.

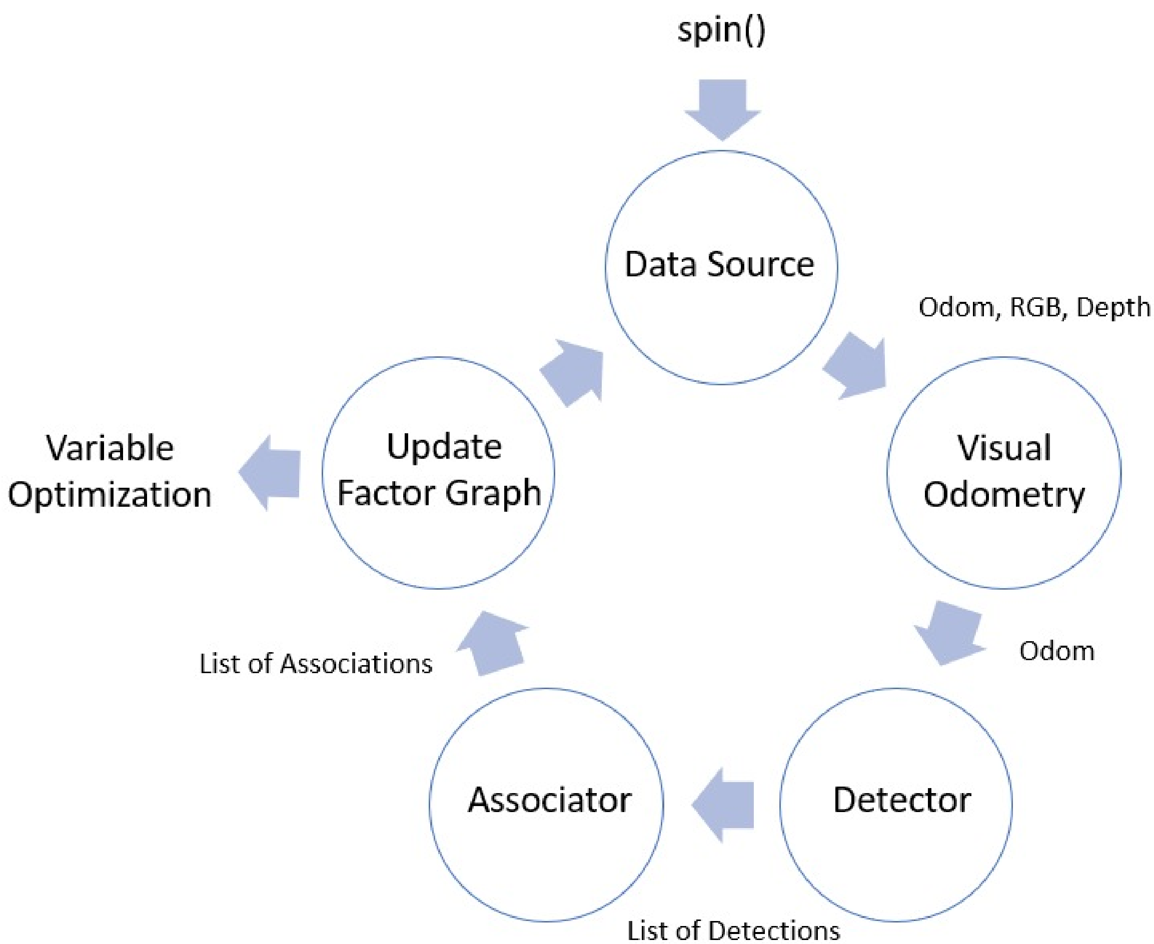


Figure 10: spin() function of QuadricSLAM

- The above figure 6 depicts the main operation of the QuadricSLAM which is the spin() function.
- The next() function of the datasource returns the current odom, RGB and depth.
- If there is no odom data, a visual odometry method could be used to generate the odom data.
- The detector takes in current RGB image and outputs a list of detections with information about the label, bounds and pose_key for each detected object. detect() function is used.
- The associator takes these detections and use IOU method to identify whether its an new object or an existing object in the graph. All the associations and unassociations are outputed by the associate() function.
- Based on the new pose and quadric information, the non linear graph is updated.
- This cycle of process continues until the dataset is completely processed.

- Based on the optimization batch setting that have been set, the unknown variables are either optimized at the end of processing all the dataset or done in an incremental fashion during each cycle.

- The values to be recorded after running the algorithm are state.estimates - which has the initial guess of the quadrics and the poses onto which the non-linear graph perform optimisation and state.labels - which has the actual label for the quadric key which we can use for evaluation purposes. Since, objects of same class appears multiple times within the graph, we cannot just use the actual label within the graph. So they are represented by a random number and this is stored in the state.labels.

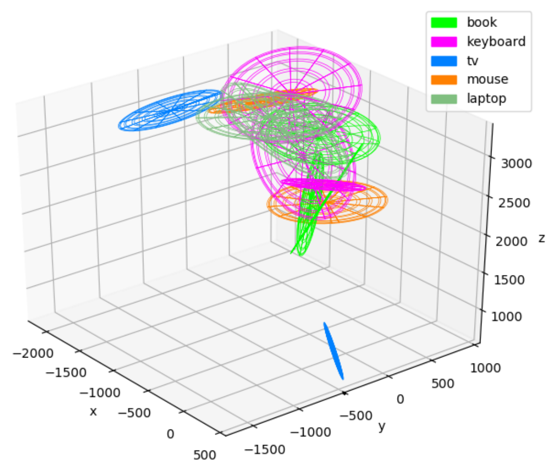


Figure 11: Batch optimization

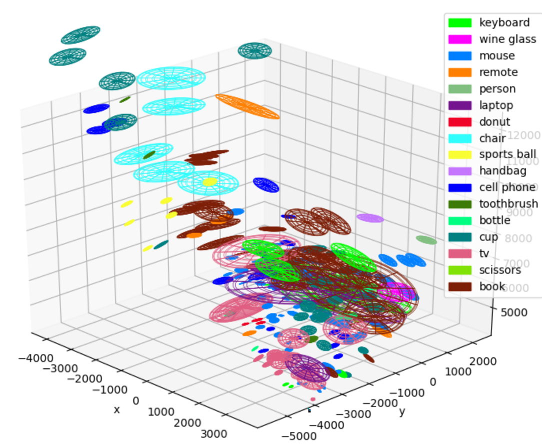


Figure 12: Incremental optimization

- The above plots represent the quadric representation of the freiburg1_desk scene of TUM RGBD dataset. In figure 11, the optimization of the factor graph is performed only at the end of reading the entire dataset. And the initial guess of the odometry value is the same as that of the provided ground truth odometry as we didn't used any explicit odometry estimation algorithm here. Because of that, the data association in each step of the data performed well in associating quadrics that belong together and thus generating 14 detected objects or quadrics in the end. Whereas in incremental optimization approach (figure 12), at each step, based on the initialized quadric from a single detection and the ground truth odometry, the factor graph is optimized. Thus the actual ground truth odometry is pulled to a wrong position to compensate for the noisy quadric detected. And this error accumulates over each time step and each detections of the same object in each data step appears at different locations in environment. This is the duplication problem in QuadricSLAM. Thus 236 quadrics are generated in the end as most of the detections of the same object couldn't be associated together.

- Another observation is that, since a single detection is used to generate a quadric, the uncertain predictions of the detector will generate some non existing objects due to the wrong label prediction. In the figure 12, objects like person, sports ball were not present in the environment. There should have been a counter to detect the number of times a particular label appears for a quadric and the final label should the most occurring one. This is possible only if the data assosciation problem is solved.

1.6 Experiments

- Below mentioned are some of the publicly available dataset for the usecase.

  – TUM RGBD dataset[5] - ground truth odom, RGB image, depth image and accelerometer data are available. Can be used for trajectory error measurement.
  (https://cvg.cit.tum.de/data/datasets/rgbd-dataset/download)

- BOP dataset - ground truth camera pose, RGB image, depth image, ground truth object poses, object bounding boxes.(https://bop.felk.cvut.cz/datasets/)

- Below mentioned are some of the evaluation metrics to test the SLAM.
  - Centroid error - Measures the euclidean distance between the actual object centroid and estimated quadric centroid. It can be calculated as root mean square deviation of the estimated object centroid from the ground truth object centroid. RMSE $E_{\text{cen}} = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\left\|\mathbf{q}_j^{\text{t}} - \hat{\mathbf{q}}_j^{\text{t}}\right\|^2}$. The estimated centroid can be derived from the 3 elements of the last column of the dual quadric representation matrix of size 4x4.[2]
  - Volume error - Measures the difference between actual volume of the object and the estimated volume of the object by comparing the overlapping between them. To compute actual volume of the object, we may need to manually fit a ellipsoid on the objects to create the ground truth. Or need to use the available 3D cuboid representation of the ground truth objects. Even though it may not give the exact quantity of the error, it can still represent the volume error which should be as low as possible.
  - Orientation error - Measures the orientation difference between the actual object ground truth and the quadric orientation parameters.
  - Trajectory error - Measures the 3D position error of the estimated trajectory and the actual trajectory. It can be calculated as root mean square deviation of the estimated pose from the ground truth pose. $\text{RMSEpos}_{\text{pos}} = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\|\mathbf{x}_i^{x,y,z} - \hat{\mathbf{x}}_i^{x,y,z}\|^2}$. If the robot is moving in a plane, we can assume z=0.[2]
  - Uninitiated objects error - This error is measured in terms of integer numbers which indicate how many objects in the environment were not mapped by the Quadric SLAM approach.
  - Association error - This error is also estimated in integers where it indicate the number of wrong assosciation of objects.
  - Duplication error - Measured in integers where it counts how many copies of the objects in the real world are duplicated in the created map.

- Trajectory error is mentioned as trajectory quality and Centroid & volume error are mentioned as landmark quality evaluation metrics in the main paper[2].

- Metrics such as centroid error, volume error, uninitiated objects error and orientation error as Match factor are mentioned in the master thesis by Kamil Kaminski[6].

- Below mentioned are some of the metrics to compare the performance of different object-oriented SLAMs.
  - Size of stored map - to compare how much space is needed to store the map containing the objects.
  - Computational power needed - this can be measured based on CPU/GPU usage
  - Computation time - How much time is required for a single step in the SLAM. That is, taking the image input and updating the internal parameters.

1.7 Evaluation

- We are using BOP dataset for our evaluation purpose as we have ground truth information about the object pose and the camera pose. We will be performing 2 experiments as of now. Measuring the centroid error with batch optimization turned on & using ground truth odometry and measuring the trajectory error with batch optimization turned on & using visual odometry generated from the images. (**CURRENT BLOCKING** - the visual odometry implemented in the github is not working. so trajectory error cannot be measured now)

- In BOP dataset, there are RGB and depth images. Also, 3 json files are present. scene_gt.json contains the object poses in terms of rotation and translation matrix for each object in a particular image. scene_camera.json contains the intrinsic and extrinsic parameters of the camera in each image. scene_gt_info.json contains the bounding box parameters for each object in each image. The bounding box parameters are in the format (x, y, width, height) where x,y is the top left corner. More details about the dataset format is given in the project website. (https://github.com/thodan/bop_toolkit/blob/master/docs/bop_datasets_format.md)

1.8 Benefits and Key Features

- Geometric SLAM approaches utilised features like ORB[7], lines[8], planes[9] to represent the environment. But they lacked the semantic information for these geometrical features. And these features were used only to estimate the robot pose and create a dense point cloud of the environment. Whereas in Quadric SLAM, the knowledge of semantic label of the geometric represented as a quadric can help in loop closure and creation of a semantically enriched object-oriented map.

- As compared to SLAM++[10] approach where prior knowledge of CAD models are used to represent the objects when they are detected, the Quadric SLAM doesn't require priors. For example, there can be different variations of chair and in SLAM++, it would be represented using the same CAD model of chair which can affect the mapping accuracy. In Quadric SLAM, the position, size and orientation could be accurately estimated from multiple views of the chairs thereby producing quadrics of different parameters for each type of chair.

- In SemanticFusion[11], each point in the point cloud is having a label and the 3d object reconstruction from the dense point cloud is performed as a post-processing step. In the proposed Quadric SLAM approach, the object representation as quadrics(mapping) is performed in an online fashion. Also, the sparse representations can help in easier storage of the map. For example, the 9 parameters of the dual quadric could be saved as a XML file.

1.9 Deficits and Challenges

1.9.1 Data association

- The challenge is determining if the object observed in the current frame has previously been viewed and added to the map or if it is a brand-new entity. If its a new one, then a new id has to be assigned to it before adding to the map.

- The main reason for the problem in data association is the duplication of the same object. It happens due to the inaccuracy in the estimated pose of the camera. At a time t, the camera may view the object with an estimated pose of p and at a later point in time $t + \Delta t$ and pose $p + \Delta p$, the camera may view the same object. This causes the same object to be appearing at 2 different positions separated by an object pose error which causes the same object to be registered with new id in the map.

- It can be partially solved by comparing the centroid of the ideal candidates for data association followed by computing the amount of overlapping between these two objects.

- Another problem is due to the error in instance segmentation when it fails to segment objects belonging to the same class cluttered together. They would be fused together as a single entity.

- This paper of QuadricSLAM[2] assumes that the problem of data association is already solved.

- From the code implementation of QuadricSLAM, we can see that the quadric IOU associator is computationally expensive as the number of quadrics within the factor graph increases. To check for data association, it had to reproject all the quadrics into 2D plane. This is due to the fact that the robot pose is uncertain and the robot can be anywhere within the map.

- This also causes another problem in factor graph. Assume there is an environment with 2 laptops at 2 different positions in environment. Assume that the QuadricSLAM had already mapped first laptop as a quadric within the factor graph. With a robot pose estimated using noisy odometry, the robot views the second laptop within its RGB image. But if the noisy odometry based pose is facing towards the scene including first laptop and if it finds the bounding box overlapping above the threshold, even the second laptop would be assigned the same quadric label as that of the first laptop. Since this created a observation factor within the factor graph as an edge that can constrain the optimisation process, the overall optimisation process becomes erroneous.

- Similar problem exists for object duplication. If the bounding box are not overlapping for the same object due to erroneous odometry, it will be registered as a new quadric with different key. This problem is evident in the image of QuadricSLAM output image mentioned in the code explanation. There we can see multiple copies of same object very close together since they didn't have any bounding box overlaps.

- Either there should be a feature within factor graph to remove constraint factor edges that violates the information provided by majority of other constraint factor edges. Or the object-centric SLAM approaches should make sure the odometry problem is well solved which can be seen in the OA-SLAM where stable ORB features are used to track the pose changes.

- To know more about data association and its challenges in object centric SLAMs, the master thesis by Kaminski[6] is helpful.

1.9.2 Noisy depth sensor data

- In Quadric SLAM, depth is an important piece of data needed for initializing the quadric parameters and also to update these parameters over long run.

- Currently, for the initialization of the quadric, the average depth of the points within the bounding box is used. This can be very noisy in each observations.

1.9.3 Noisy detection model

- The appearance of objects in the training data and in the real world may affect incorrect classification labels. The uncertainty can be due to the environmental factors like lighting or due to the shaking or blurring of the camera.

- The bounding boxes generated may not be stable between multiple frames as the robot is continuously in motion. Sometimes even the smaller objects may not be detected by the detection model which can be due to low resolution of the camera causing it to be blurred out. The noise is assumed to be Gaussian in the factor graph whereas it maybe non-Gaussian in actual scenario.

- In the followup paper of Quadric SLAM[4], the authors rejects the objects having bounding boxes with high variances to reduce the error from mapping section which can affect the robot pose estimation in the factor graph. The errors in mapping and in pose estimation can affect each other.

1.9.4 Noisy odometry data

- The odometry that is passed into the front-end of factor graph should be as stable and good as possible as its error can propagate to the mapping component also as factor graph solves both mapping and pose estimation jointly.

- In the initial paper of Quadric SLAM[2], they are using raw odometry value available from the wheel. In the implemented code of Quadric SLAM, either this wheel odometry or CV2 library based visual odometry function is used to estimate the odometry between RGB frames. In the followup paper[4], they have used ORB-SLAM2 as the odometry generator with the loop closure disabled.

- In general, the noise in the odometry can affect the non-linear optimization of the factor graph and should be taken care of through implementing a stable and accurate underlying odometry estimator.

1.9.5 Effects of object occlusion

- When an object is occluded and still a bounding box is generated for the visible part of the object, the quadric parameters would be fitted to that particular subsection of the object which is inaccurate. The centroid error would be evident in this case. This is due to the fact that we don't have prior knowledge of how the entire surface of the object would look like which can help in guessing the surface of the occluded region of the object.

1.9.6 Effects of dynamic objects

- If the object is moving within the environment during the Quadric SLAM procedure, then it will cause the detection of the object to be all around the environment causing the dual quadric parameters to be unstable. This also affects the robot pose estimation as the errors in mapping and localization are reduced jointly in the factor graph.

2 OA-SLAM

- The OA-SLAM[12] stands for Object Aided SLAM which utilizes the objects as a key feature for aiding mapping and camera relocalization. It is an improved version of quadric SLAM where the feature points within the environment are also mapped along with the quadric shapes(ellipsoids, cuboids) to improve object tracking and pose recovery in case of tracking failures during sudden motions.
- This method is built on top of ORB-SLAM2. ORB-SLAM utilizes visual bag-of-words keypoint descriptors to compare the ORB features in the current scene with the reference map of the environment. The disadvantage is its restricted invariance to viewpoint changes which makes it difficult to localize when some landmark points are not visible in the current image frame.
- The low-level landmark points are combined with the quadrics of the object generated through object detection methods to form high-level landmarks where objects can be used as anchors for mapping and localization. This can help to improve the viewpoint invariance.
- Even though the representation of the environment with the help of key points helped in efficient computations in ORB-SLAM, it lacked the semantic meaning which could be useful for relocalization in a dynamic environment.

2.1 Previous work

- Previous works on sparse, dense and semi dense
- Previous work on quadric parameters estimation from bounding boxes of object detections.
- Previous work on initial quadric parameter estimation.
- Previous work on camera pose estimation utilizing objects using a pre-built object map.
- Previous work on semantic segmentation on point cloud as a post-processing step to generate dense object maps. Cannot be used for localization as its a post-process step.
- Previous work of QuadricSLAM[1] was mentioned and the disadvantage was the assumption of the data association is solved.
- Previous works on fitting a predefined CAD model onto the object once it is detected.
- Previous work focuses on dense point cloud mapping of objects whereas we focus on an approximate representation of the object properties in terms of position, size and orientation that could be used in most of the applications except where manipulation of the object is needed.

2.1.1 ORB SLAM

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2.1.2 Structure Aware SLAM using Quadrics and Planes[13]

- As a continuation of quadricSLAM, Sünderhauf et. al. also looked into extracting planes from the environment which can act as an extra constraint combined with the feature points within the factor graph[13].
- This concept of infinite planes was first introduced into factor graphs as a least-squares optimization problem in the paper by Kaess[9]. And later, Taguchi et. al. presented a SLAM method where a combination of planes and points can be used to register 3D data, since a single plane can be used to replace a lot of inlier 3D points which can help in faster computations and compact representations.[14]
- In this work, planes are also considered as an important feature which is the most common feature occurring in indoor environments. A plane can represent a big region of the environment, especially in cases where there are very few objects within the environment to be mapped and used as anchors.
- These planes can be used to create three additional constraints. Constrain between the points lying on the plane and the plane parameters. Constrain between the object and the supporting plane parameters. Constrain between two planes.
- The following section explains about the mathematics behind quadric and plane representations along with how the constraints can be added to the factor graph as a non-linear least squares problem. The section is a summarized version of the content in section 3 of the "Structure Aware SLAM using Quadrics and Planes" paper[13].
- From the previous section on QuadricSLAM, we have seen that the closed-form equation of quadric with tangential planes is given by $\pi^T Q^* \pi = 0$ where Q^* is called as dual quadric representation. There are 9 unique elements within this symmetric matrix that needs to be estimated through error minimization. So the error vector generated is 9 dimensions.

$$\mathbf{Q}^* = \mathbf{T}_Q \mathbf{Q}_c^* \mathbf{T}_Q^T = \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}^T & 1 \end{bmatrix} \begin{bmatrix} a^2 & 0 & 0 & 0 \\ 0 & b^2 & 0 & 0 \\ 0 & 0 & c^2 & 0 \\ 0 & 0 & 0 & -1 \end{bmatrix} \begin{bmatrix} \mathbf{R}^T & \mathbf{0} \\ \mathbf{t}^T & 1 \end{bmatrix} \tag{4}$$

- Since we are fixing the quadric to be ellipsoid in this application, the dual quadric representation Q^* could be written as 4. T_Q is the transformation matrix that transforms the ellipsoid from its origin by rotating and translating it. Q_c^* is the ellipsoid located at the origin with radius a,b and c. The last element of Q_c^* is made -1 to represent the dual quadric matrix as an ellipsoidal equation.

$$\mathbf{Q}^* = \mathbf{T}_Q \mathbf{Q}_c^* \mathbf{T}_Q^T = \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}^T & 1 \end{bmatrix} \begin{bmatrix} \mathbf{L}\mathbf{L}^T & \mathbf{0} \\ \mathbf{0} & -1 \end{bmatrix} \begin{bmatrix} \mathbf{R}^T & \mathbf{0} \\ \mathbf{t}^T & 1 \end{bmatrix} \quad \text{where} \quad \mathbf{L} = \begin{bmatrix} a & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & c \end{bmatrix} \tag{5}$$

- Further, to make sure that the first 3 diagonal elements of the Q_c^* matrix are positive eigen values during optimization process in factor graphs, the equation 4 is updated to 5 so that it guarantees positive values.
- Now updation of Q^* means updating T and L where T is the transformation matrix of 6 parameters(3 rotation and 3 translation) and L is a diagonal matrix with 3 parameters(a, b, c scale parameters). Thus the 9 dimension error can be split into 6-dim and 3-dim errors for efficient computation.

$$\mathbf{Q}^* \oplus \Delta\mathbf{Q}^* = (\mathbf{T}, \mathbf{L}) \oplus (\Delta\mathbf{T}, \Delta\mathbf{L}) = (\mathbf{T} \cdot \Delta\mathbf{T}, \mathbf{L} + \Delta\mathbf{L}) \tag{6}$$

- The updation of quadric parameters in Q^* can be simplified as in equation 6. The Δ values indicate the update value. In the case of L, the updation operation is addition based on the first 3 values of the 9 dim error vector and in case of T, it needs to perform the transformation operation for the updation based on the last 6 values of the 9 dim error vector.

- This representation of Q^* in terms of T and L also helps to add initial prior information about the properties of the object into the factor graph. The size info can be initialized in L matrix and the rotation and translation info can be initialized in T matrix.

- Next, we have to represent the planes in mathematical form. Inspired by the work on infinite planes by Kaees[9], an infinite plane is represented by normalised homogeneous coordinates $\pi = \begin{bmatrix} a & b & c & d \end{bmatrix}^T$ to have a compact representation. n is the normal vector $\mathbf{n} = \begin{bmatrix} a & b & c \end{bmatrix}^T$ and d is the distance to the origin. This normal vector can be optimised using the rotation matrix algebra.

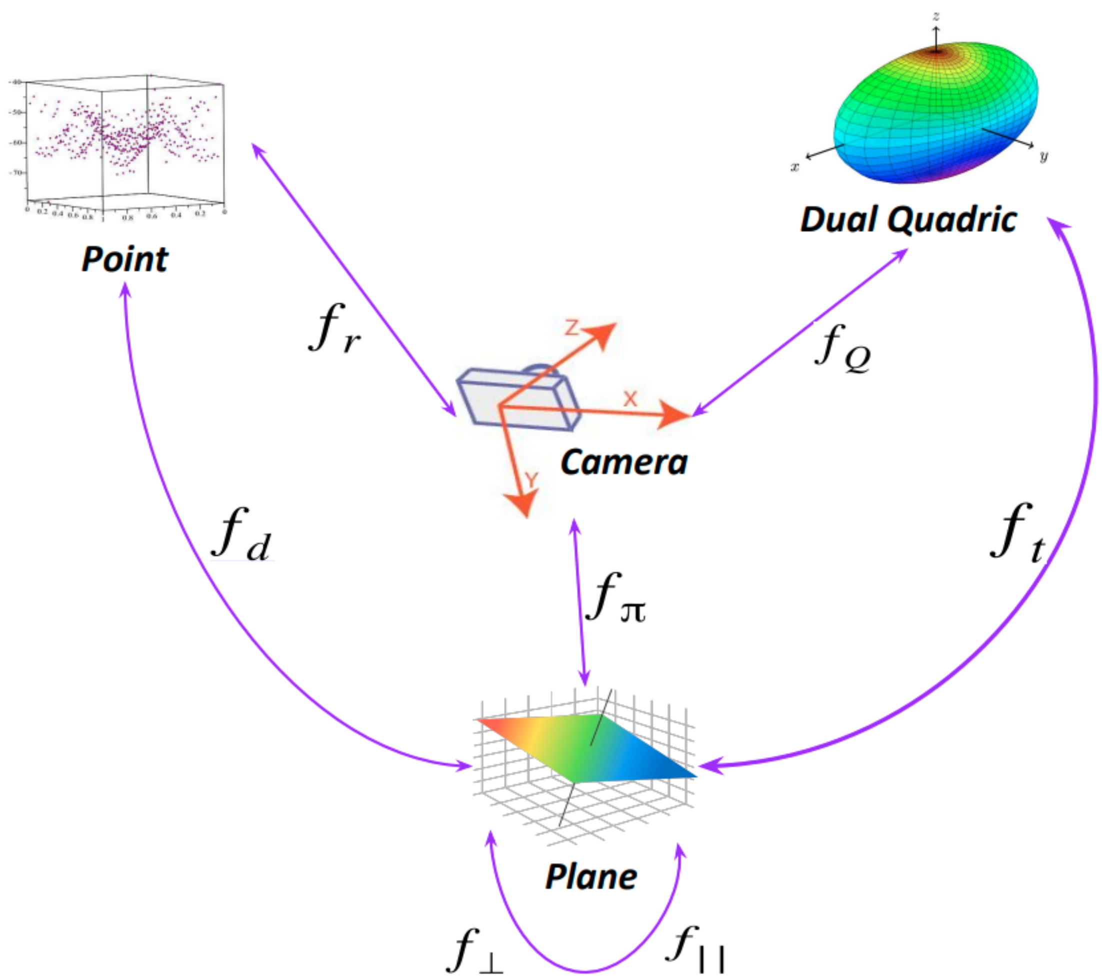

Figure 13: Factor graph containing points, planes and objects [13]

- The above figure 13 shows the factor graph containing the nodes/ variables representing camera pose, 3D points, quadric parameters, plane parameters that need to be estimated and the connecting edges which represent 7 different types of factor constraints($f_r, f_Q, f_\pi, f_d, f_t, f_\|, f_\perp$).

- **1. Observation of points(f_r):** The 3D points observed by the camera at a particular pose is to be registered within the factor graph. The equation tries to minimize the reprojection error.

$$f_r\left(\mathbf{x}_w, \mathbf{T}_c^w\right)=\left\|\mathbf{u}_c-\Pi\left(\mathbf{x}_w, \mathbf{T}_c^w\right)\right\|_{\boldsymbol{\Sigma}_r} \tag{7}$$

In the above equation 7, x_w represents the 3d point in world coordinates, T_c^w represents the transformation matrix of the pose of the camera w.r.t the world that can map the observed point in the current pose c to the world coordinate system. The error is calculated between the pixel location of the point u_c in the current pose c and the reprojected point from the world coordinate into the camera frame using the function $\Pi()$. The error function is the Mahalanobis norm $\mathbf{x}^T\boldsymbol{\Sigma}^{-1}\mathbf{x}$ where Σ is the uncertainty matrix associated with the factor. Mahalanobis norm takes the covariance structure of the data into consideration while reducing the reprojection error where the distance to the distribution is utilized instead of the distance to a single point as in the euclidean norm.

- **2. Observation of objects(f_Q):** The objects in this case are the ellipsoids. So need to reduce the reprojection error between the conic of the viewed object and the reprojected conic from the ellipsoid in the world cordinates at a particular camera pose c. More details on the conic equation formation in mentioned in the above section on QuadricSLAM.

$$f_Q\left(\mathbf{Q}^*, \mathbf{T_c^w}\right)=\left\|\mathbf{C}^*-\mathbf{C}_{\mathbf{obs}}^*\right\|_{\mathbf{F}}=\sqrt{\mathbf{Tr}\left(\left(\mathbf{C}^*-\mathbf{C}_{\text{obs}}^*\right)\left(\mathbf{C}^*-\mathbf{C}_{\text{obs}}^*\right)^{\mathbf{T}}\right)} \tag{8}$$

In the above equation 8, the norm being used is Frobenius norm. It is measuring the magnitude of the matrix or in other words the root of summed squares of the elements of the matrix. Can be used to check for residuals. Since we are trying to reduce the reprojection error, ideally the value should be 0 or close to 0.

- **3. Observation of planes(f_π):** The distance between observed plane π_{obs} at a particular camera pose c and the plane parameters in the world coordinate π projected into the camera frame is minimized. Since the normal vector n is used to describe the plane, the distance measured is based on the rotational distance in rotation space between the normal vector for π and π_{obs} which is explained in the work by Kaess[9].

$$f_\pi\left(\pi, \mathbf{T_c^w}\right)=\left\|d\left(\mathbf{T}_c^{w-T}\pi, \pi_{obs}\right)\right\|_{\Sigma}^2 \tag{9}$$

- **4. Point-plane constraints(f_d):** If there is a certainty that a point lies on a plane, then the constraint between the point and the plane can be established as minimizing the orthogonal distance between the normal vector n representing the plane and a vector formed between the point x and a random point x_o on the plane.

$$f_d(x, \pi)=\left\|\mathbf{n}^T\left(\mathbf{x}-\mathbf{x}_o\right)\right\|_\sigma^2 \tag{10}$$

In the above equation 10, the dot product between the two vectors is taken. The normal vector n is perpendicular to the plane surface and if the point x is on the plane surface, then the vector connecting x and x_o would be perpendicular to the normal vector and the dot product would be 0.

- **5. Supporting plane constraints(f_d):** In the real world, all the objects on the floor or on the walls are supported by a plane. For example, a clock is supported by a wall plane and a computer is supported by a table plane. This knowledge is exploited to create a constraint between the object and the supporting plane. The same equation which was used to define dual quadrics, i.e. a quadric is enclosed by tangential planes is used here also.

$$f_t\left(\pi, \mathbf{Q}^*\right)=\left\|\pi^T\mathbf{Q}^*\pi\right\|_\sigma^2 \tag{11}$$

- **6. Plane-plane constraints($f_\parallel, f_\perp$):** Based on the Manhattan assumption, 2 planes can either be perpendicular or parallel.

$$
\begin{aligned}
f_{\|}(\pi_1, \pi_2) &= \left\| \left| \mathbf{n}_1^\top \mathbf{n}_2 \right| - 1 \right\|_\sigma^2 \quad \text{for parallel planes} \\
f_{\perp}(\pi_1, \pi_2) &= \left\| \mathbf{n}_1^\top \mathbf{n}_2 \right\|_\sigma^2 \quad \text{for perpendicular planes}
\end{aligned}
\tag{12}
$$

In the above equation 12, the dot product between the normal vectors of plane 1 and 2 is taken. In case of parallel planes, the dot product would be 1 and the error term would be 1-1=0 and in the case of perpendicular planes, the dot product would be 0.

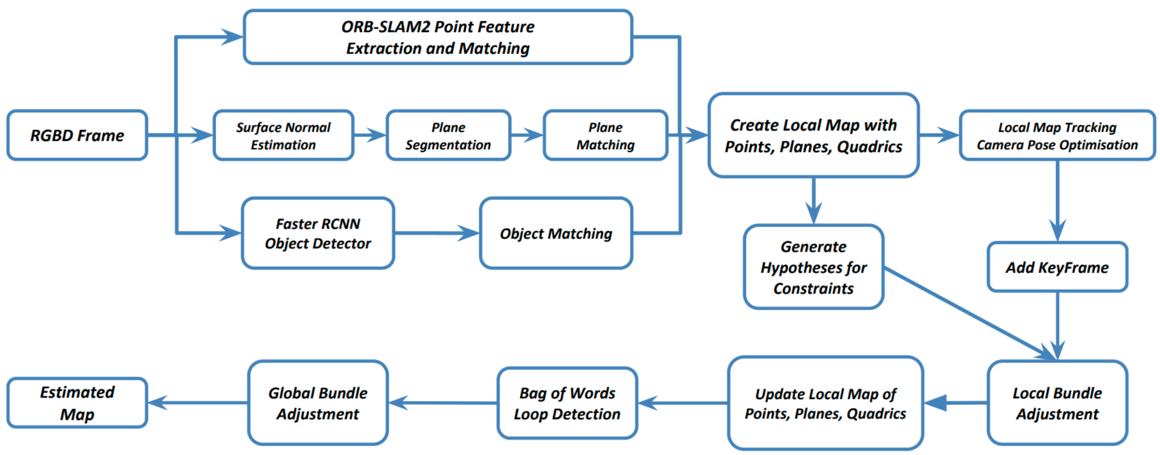

Figure 14: SLAM pipeline [13]

- The above figure 14 represents the internal pipeline of the slam. This architecture is based on ORB-SLAM except for the fact that the plane and object detection is added in parallel to the point detection at the input side of the pipeline. The optimization step happens in an incremental fashion whenever a new keyframe is added along with its observations (basically an input image and the observed objects, planes and points). Loop closures are detected based on ORB feature matching using the bag of words method as in ORB-SLAM. The input is an RGBD image instead of an RGB image in ORB SLAM for the purpose of plane detection and object quadric initialization. The authors also plan to remove the use of RGBD images and use monocular RGB images in future work to perform depth estimation and semantic segmentation on single images.

- **1. Observation of points:** This is the same as in the ORB-SLAM. Unique ORB features are identified, tracked and matched(data-assosciation) between images. The depth initialization for these points can be made available from the depth channel if an RGBD image is provided as input or can estimate the depth between consecutive RGB images.

- **2. Observation of objects:** A pre-trained Faster-RCNN is used to generate the bounding boxes through object detection. The conic is fitted into the bounding box as explained in the previous section on QuadricSLAM. To deal with noisy detections, the object is initialized only if it is having a confidence of above 95% for a class label. Also to solve the data association problem if multiple copies of the same object are present, a nearest neighbour approach is used to find whether they are 2 separate objects or inconsistent detection of the same object.

- **3. Observation of planes:** Usually planes are detected using RANSAC which not be sufficient to meet the runtime requirements in SLAM to perform online operations. Also we need a finite boundary for the planes instead of infinite plane representation.

- Trevor et.al [15] utilizes the availability of organized point clouds(2D image with depth channel as compared to LIDAR point clouds) to perform segmentation which can reduce the time taken for neighbourhood searching step in unorganized point clouds. Each pixel is assigned a label and 2 pixels can have the same label if they are similar. In the first pass, the first row and first column of the image point cloud are assigned labels based on their similarity with immediate neighbours. After that, for each other pixel, its top and left neighbours are compared for similarity. If similarities are detected, then in the second pass of the algorithm, the labels are merged. To detect planar surfaces from these point clouds, for each point belonging to labels having a large surface(corresponding to floor, wall, ceiling), a surface normal is computed to represent the plane equation. The fourth plane component d is also computed using the dot product of the surface normal and the point's coordinate. Then the angular distance(dot product) between the surface normals and the L1 norm of the d distance parameters of the 2 points as the similarity factor to identify points belonging to a connected plane based on certain thresholds. Since smooth curved surfaces are also getting detected through this method, a max allowable curvature threshold is also set. To identify large surfaces, the min inlier point threshold is set. Later a plane refinement step is also performed to get a less noisy boundary by taking in unsegmented boundary pixels also. The authors also mention that the colour could be also used as a similarity measure by comparing in the Euclidean space.

- For data association in the factor graph, all planes are considered as the number of planes in an environment is assumed to be sparse and also the viewpoint change of the planes between the subsequent image frames is assumed to be less. The data association can be performed by comparing the normal vectors and distance parameters of the plane equations.

- **4. Point-plane constraints:** After performing the plane detection, the inlier points are detected by comparing the distance of the point from the camera with a threshold value. This is because the farther the point is from the camera, then the depth will have higher uncertainty. If it satisfies the inlier condition, then it is added to the factor graph as a point-plane constraint.

- **5. Supporting plane constraints:** The supporting infinite plane for the object is identified by comparing the orthogonal distance of the centroid of the object quadric with the plane. If it is less than a threshold defined by $max(20cm, a, b, c)$, then the object is supported by the plane. a, b, c is the radius of the ellipsoid and hence the threshold is dependent on the size of the quadric.

- **6. Plane-plane constraints:** For establishing plane-to-plane constraints, every plane is taken into consideration(due to the sparsity of the planes) and a parallel or perpendicular constraint is established if the angle difference between the normals of the plane is within a certain window range. The uncertainty for this constraint is set to high so that the factor graph won't force them to be always perpendicular or parallel but act as a good prior for relative orientation between the planes.

- In the evaluation part, a qualitative comparison is performed as we don't have the ground truth mapping data available for the TUM-RGBD dataset. In quantitative comparison, only RMSE Absolute Trajectory Error (ATE) is estimated. The qualitative comparison is performed because the real world cannot be exactly and semantically mapped for the ground truth. So the best solution is to create a virtual environment in simulators like Gazebo or frameworks like BenchBot(link).

2.2 Benefits and Key Features

- Useful in AR applications where the objects and points can be used to relocalize the camera pose when the camera tracking fails.

- Virtual objects can be placed in the real world over the objects identified during the SLAM.

- The proposed approach require only RGB camera instead of RGB-D camera which is very helpful in deployment in devices like mobile phones.

- The object mapping and camera pose is estimated on real time.

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