RESLAM: A real-time robust edge-based SLAM system

Introduce

Edge-based method has larger convergence basin and stability under illumination changes

The author proposed a complete SLAM pipeline comprises trajectory estimation, loop closure and re relocalisation.

Proposed Framework

- The whole framework

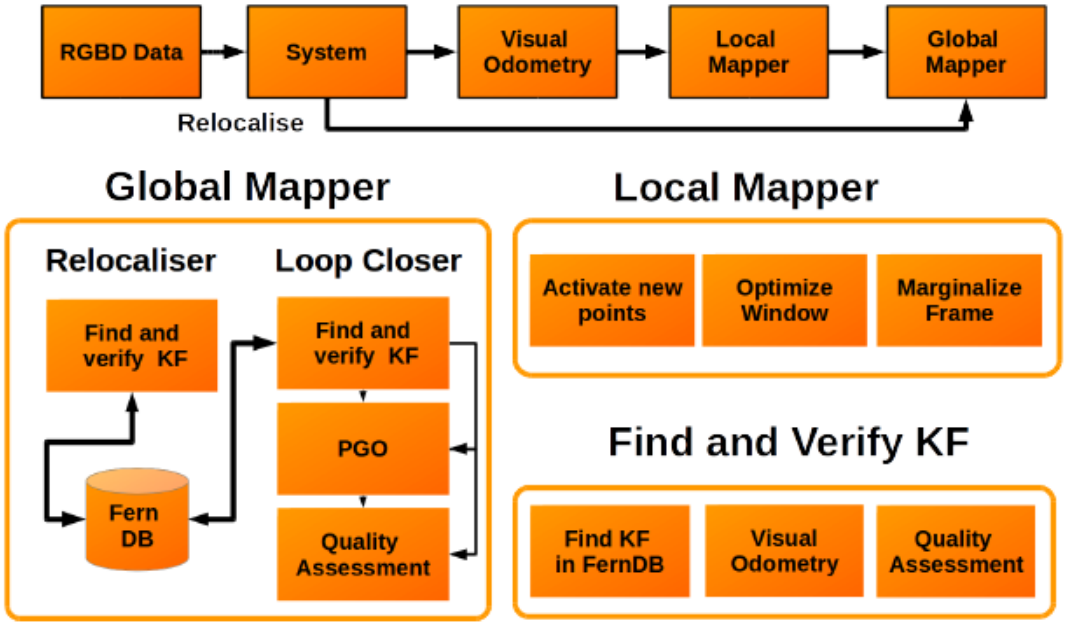


Fig. 2. RESLAM comprises three main components: (i) the VO modul estimates relative camera motion, (ii) the Local Mapper manages keyframes and optimizes a local window and (iii) the global mapper stores a global map and performs loop closure and relocalisation.

- System: receive rgbd and preprocess step(detect edges).
- VO: estimate relative pose from current to keyframe.
- Local Map: slide window for refine edge depth, pose and K.

    - Global Map: for loop closure.
    - Relocalisation: if VO failed, receive data from system.
- Edge-Based VO
    - In each frame, detect Canny edges, estimate relative pose by align with the closest edge.
    - precompute the Euclidean distance to the closest edge at each pixel position using the distance transform and minimizing error for the set of all edges.

$$E_{p_i} = \mathcal{D}_j(\tau(\xi_{ji}, p_i, Z_i(p_i))),$$

$$\xi_{ji}^* = \underset{\xi_{ji}}{\operatorname{argmin}} \sum_{p_i \in \mathcal{E}_i} \delta_H E_{p_i},$$

    - Since detections often differ between frames, so drop a potential outlier if E > theta.
    - Motion Assumptions:
        - evaluate five different initializations for relative pose
    - Alignment Failures:
        - may due to a partly or fully covered sensor, very aggressive motions or reflective or sunlit surfaces
        - switch the system to relocalisation mode
- Instead of detecting edges on each pyramid level separately, we only detect edges and explicitly compute the DT on the highest level

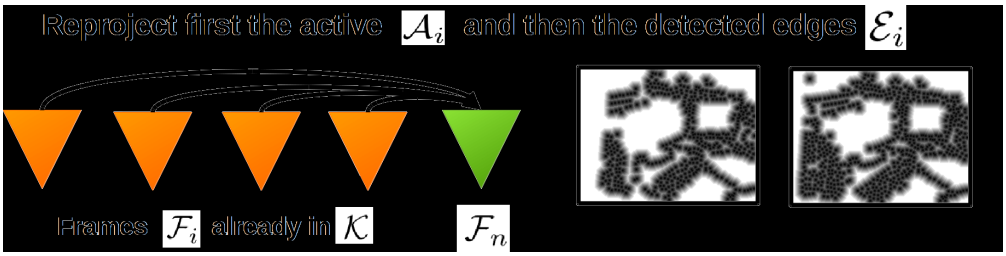
> The edges are then reprojected to lower levels through camera intrinsics

    - reduces computational cost
    - addressing the robustness issue
- Local Mapper

> optimize over a window, jointly refine the depths of all active edges, poses and the camera intrinsics with a Gauss-Newton optimization algorithm

    - Edge Management

        - have a set of around 10k-20k detected edge pixels with valid depth in slide window
        - maintain a distance map for drop old keyframe



        - activate an edge if its reprojection is close to an edge detection and not close to an
          already activated edge

- Keyframe
    - Creation

      > create many 5-15 KFs per second and cull them later

        - mean square optical flow measures changes in the field of view
        - mean flow without rotation measures occlusions
        - number of edge reprojections distance
    - Marginalization
        - has less than theta active points
        - compute a distance score of newest two KFs
        - marginalize all its active edges on marginalized KF
- Loop Closure
    - find loop closure candidates by follow the random-fern-based bag of words approach
    - set up a pose graph optimization optimize by ceres
    - verifying if the loop closure is correct

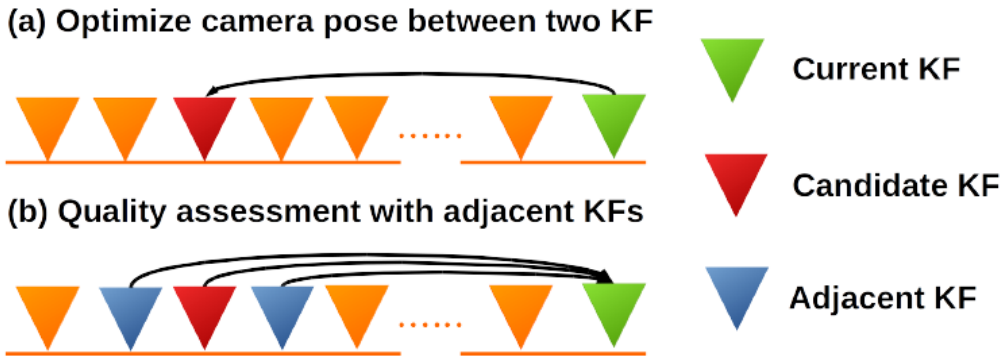


Fig. 4. Whenever we find a candidate KF in the Fern database, (a) we estimate the relative camera motion between the current (green) and the candidate KF (red). (b) Before and after PGO, we assess the quality by reprojecting the edges from the candidate KF and its adjacent KFs (blue) to the current KF.

Result

runs in real-time at 30-35 Hz.

optimize the relative camera poses in a 3 level coarse-to-fine scheme with maximum resolution of 640*480 px.

Comparison of the Absolute Trajectory Error $[cm]$

	BF [9]	RGBDTAM [8]	DVO-SLAM [7]	EF [6]	ORB2-SLAM [4]	RGBDSLAM [5]	REVO [10]	Edge+ICP [20]	Our Methods			
Seq.	Direct				Features		Edges		VO	LM	LC	All
fr1/xyz	-	1.0	1.1	1.1	**0.8**	1.3	6.8	1.6	7.4	2.4	2.2	1.1
fr1/desk2	-	**4.2**	4.6	4.8	2.2	4.2	8.2	6.0	7.1	6.3	5.4	4.8
fr2/desk	-	2.7	1.7	7.1	**0.9**	5.7	8.9	9.5	3.5	3.4	3.6	1.9
fr2/xyz	**0.4**	0.7	1.8	1.1	0.8	0.8	1.0	-	0.9	0.5	0.8	0.5
fr3/office	2.2	2.7	3.5	1.7	**1.0**	3.2	11.0	-	13	7.8	4.2	3.5
icl/lr-kt0	**0.6**	-	10.4	0.9	0.8	2.6	24	5.4	6.5	3.2	2.2	2.1
icl/lr-kt1	**0.4**	-	2.9	0.9	1.6	0.8	2.3	0.9	1.3	1.9	2.5	1.7