Real time Localization Method Research with Monoslam and BIM Model

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Abstract: Outdoor navigation technologies based on GPS and Beidou has been very mature. However, due to the weakness of satellite signal and refraction, they can’t satisfy the needs of indoor localization and parking area navigation in large commercial buildings. Most indoor localization technologies, such as Bluetooth and Wi-Fi, are based on active equipment. Due to the implementation cost, they can’t be widely deployed. In recent years, SLAM has been greatly developed and applied in the field of robotics and autonomous driving. For technologies such as stereo SLAM and Lidar SLAM require additional equipment, and meanwhile large scale computing will happen during point cloud matching, they are not suitable for civilian mobile usage. Considering the BIM technology, which can provide accurate 3D data of buildings, are widely used gradually, a real-time localization method combining monocular SLAM and BIM model is proposed to complete vision-based initial localization. First, we create the BIM model with the design drawings, extract the visible edge lines of model, and establish a 3D line feature database; then, intercept the key frames of the mobile camera, and extract the edge line and line feature descriptors from image, match the line features between key frames, triangulate the matched line segments, get the 3D line coordinate in first frame, mistake filter will be rolled out between multiple frames; finally, match the reconstruction result with line feature database form BIM model, register the initial position. This method can quickly and effectively perform the registration of monocular images and BIM models, get the initial position in complex spaces, and support the application scenarios such as indoor navigation, equipment maintenance, facility management, and construction monitoring.

1. Introduction

As a necessary technology of informatization and project management optimization in construction industry, the BIM (Building Information Modeling) has gained much attention from management departments. BIM becomes a necessary tool for future construction projects, especially prefabricated buildings, and also provides the data basis for smart building and smart city information system.

Since there is faint GPS and Beidou satellite signal inside the buildings, most of the indoor localization technologies are based on active signal equipment, such as Wi-Fi, Bluetooth, ultrasonic, RFID, structured light. Due to requirement for additional cost of equipment and the accuracy is interfered by signal strength and building barrier, these traditional indoor localization technology are not widely implemented. This restricts the usage of BIM in the area of operation management with mobile device, navigation inside buildings, underground parking lot navigation and so on.

SLAM (Simultaneous Localization and Mapping) is a method for real-time localization and map building of the surrounding environment in unknown environments. Common sensing devices,
including Lidar, depth camera, stereo camera and monocular camera, are used in autonomous driving and robot visual navigation systems. Because of low cost of devices, monocular vision is suitable for scene recognition and localization with mobile equipment. The key of monocular vision location is image feature detection. A common technology combination is a feature point detectors such as Harris corner detection [1] with a feature measurement algorithm, the popular choices includes SIFT, SURF (Speed up robust feature) algorithm [4, 5] and ORB (Oriented fast and rotated BRIEF) feature algorithm [6]. However, due to the low texture features in the interior of the building, the efficiency of feature method based on points detection is reduced, line feature method is used for image recognition, the line feature detection includes EKF (extended Kalman filter) [7], Canny edge detector [8], Hough transform [9], LSD (line segment detector) line segment detector [10, 11, 12], EDLines line feature detection [13] and LBD (line strip descriptor) [14]. There are also a lot of researches focused on the registration of point cloud and BIM model [15], and construction process schedule management based on image registration [16,17,18,19,20,21]. Because the localization based on image matching needs a large number of image feature libraries in advance [22], it will lead to the high cost and low efficiency in large-scale scene; 3d reconstruction based on vision using multiple image feature matching results to establish 3d point cloud, matching the results with point cloud library [23], there is still a computational complexity problem in large-scale scene. Therefore, this paper proposed a method of indoor localization based on 3D point line feature matching with BIM model, to make full use of the data results of intelligent building, improve the efficiency of indoor identification and localization, and solve the indoor location and navigation initialization.

2. Principle and Method
The method proposed in this paper comprises by four steps:

First step, Detect and extract line segments by using Ed-line feature extraction method, and match the extracted line segments by calculating the LBD operator;

Second step, Calculate the ORB descriptors for the feature points on two images, and then solve the camera's motion parameters by using the pole constraint;

Third step, using triangulation to estimate the 3D coordinates of the matched feature points and the line segments;

Forth step, initialize the camera position by matching 3D line segments from step 3 with the models from BIM reference library.

2.1. Extraction and Matching of Feature Segmentation
EDLines line extraction algorithm and LSD (Line Segment Detector) line segment detection algorithm are common line extraction methods. The LSD algorithm detects the pixel point set with searching large gradient changes in the image, and then verifies the solution by assuming the parameters, merges the pixel point set with the error control set, and then adaptively restricts the number of error detection. EDLines straight line extraction algorithm bases on gray image, it extracts continuous pixel points by edge detection, edge drawing (Edge detection by Edge Drawing) algorithms, then the least square method is used to connect pixel points and fit line segments. Finally, the Helmholtz principle [28] proposed by Desolneux is used to restrict the false of detection. Experiment shows that the time cost is only about 1/10 of LSDs, while the results of EDLines have a similar quality with LSD method. Though the LSD has also carried on the optimization upgrade [29], the later researches have compared the two algorithms' straight line detection performance, obtained that the EDLines algorithm has a better performance on the power line extraction problems [24]. The experiments from domestic scholar [25, 26] show that the EDLines algorithm has a slight advantage over the LSD at comprehensive performance, and can obtain better straight line extraction results for different scene images, especially the extraction of long straight lines, EDLines has higher accuracy and efficiency.

This paper selected the LBD line band descriptor algorithm [27] to define the line segment feature, and based on the descriptor, matches the line segment feature in the two graphs. The first step of the LBD method, using the EDLines algorithm to extract features; the second step is feature description,
reference the SIFT, uses the statistical gradient histogram as the descriptor. The pixel gradient is counted and the average vector and standard variance of the statistic are calculated as the descriptor. The details are as follows:

1) Build scale space. An N layer scale image pyramid is constructed by a set of scale factors and Gaussian blurring, the Gaussian blurring causes scale space of the current layer of image is the convolution result of the original image and the Gaussian function $G(x, y)$. The Gaussian function:

$$G(x, y) = \frac{1}{\sqrt{2\pi \sigma^2}} e^{-\frac{(x-x_0)^2 + (y-y_0)^2}{2\sigma^2}}$$  \hspace{1cm} (1)$$

For each layer above layer two, the Gaussian blurring parameter $\sigma$ is $\sqrt{2}$ times of next layer. And the bottom layer of image pyramid is the origin picture, from bottom to top, the side length of upper layer is reduced as $1/\sqrt{2}$ as the inferior layer.

2) A set of line segments is obtained by extracting the line features on each layer in image pyramid by EDLine algorithm. Then, the lines in the scale space are reconstructed to find the corresponding segment. If any line segment taken from different scale spaces are identical in the image (e.g., the same region of the image, and in the same direction), then a unique ID was assigned on it and stored it into a same LineVec variable.

![Figure 1. Line segment detection in scale spaces.](image)

The final result is a set variable of LineVec, as shown in figure 1, different segments in the same LineVec is the same line segment in different scale space. So the line segments in same LineVec have the same direction and corresponds the same construction in original image.

3) The local rectangular region around the line segment was choosen as the line segment support region LSR (line support region). The LSR region is divided into a group of bands \{B_1, B_2, B_3……B_m\}, the width of per band is w. The example shown in figure 2 is a LSR area map with m =5, w =3; vector $d_L$ in diagram represents the direction of line segments, $d_L$ indicate the vertical direction of $d_L$ in clockwise side, the origin of the local coordinate system was set at the midpoint of the line, using this local 2D-coordinate system to distinguish parallel lines with opposite gradient directions and keep the descriptor rotate unchanged.
projection the gradient of pixels in the LSR into the local coordinate system by:
\[ \mathbf{g}' = (\mathbf{g} \cdot \mathbf{d}_L, \mathbf{g} \cdot \mathbf{d}_L)^T = (\mathbf{g} \cdot \mathbf{d}_L, \mathbf{g} \cdot \mathbf{d}_L)^T \]  
(2)

The \( \mathbf{g} \) is the pixel gradient in the picture coordinate system, \( \mathbf{g}' \) is the pixels' gradient in the local coordinate system. Then two Gaussian functions are applied to each row in the \( \mathbf{d}_L \) direction: firstly, a global weight coefficient is arranged on the line \( \mathbf{i} \) in the LSR:
\[ f_g(i) = \left(1 / \sqrt{2\pi} \sigma_g \right) e^{-d_i^2/2\sigma_g^2} \]  
(3)

The \( d_i \) represents the distance from the \( \mathbf{i} \) row to the central row in the LSR, and \( \sigma_g = 0.5(m \cdot w - 1) \); next, assigned for each row in the band \( \mathbf{B}_j \) or the adjacent bands \( \mathbf{B}_{j+1}, \mathbf{B}_{j-1} \), a local weight coefficient is assigned as:
\[ f_j'(k) = \left(1 / \sqrt{2\pi} \sigma_j \right) e^{-d_k^2/2\sigma_j^2} \]  
(4)

The \( d_k \) is the distance from line \( \mathbf{k} \) to the center point of band \( \mathbf{B}_j \), \( \sigma_j = w \).

4) Construct LBD line band descriptor. The line band descriptor \( \mathbf{BD}_j \) consists of \( \mathbf{B}_j \) and its two adjacent bands \( \mathbf{B}_{j+1} \) and \( \mathbf{B}_{j-1} \). Parts outside the LSR area are not considered in the algorithm when calculating the top band \( \mathbf{B}_1 \) and bottom band \( \mathbf{B}_m \) in the strip of bands. After \( \mathbf{BD}_j \) calculations, connect the results as a LBD line band descriptor: \( \mathbf{LBD} = (\mathbf{BD}_1^T, \mathbf{BD}_2^T, ..., \mathbf{BD}_m^T)^T \). For the \( k \)th nearest adjacent rows of band \( \mathbf{B}_j \), accumulative total of four directional gradients of pixels in the row:
\[ v^{l_j} = \lambda \sum_{g_{d_i} > 0} \mathbf{g}_{d_i}, \quad v^{2_j} = \lambda \sum_{g_{d_i} > 0} -\mathbf{g}_{d_i}, \quad \text{Gaussian coefficient} \; \lambda = f_g'(k) f_j'(k) \]  
(5)

By accumulating the gradient information of all rows related to the band \( \mathbf{B}_j \), construct the following strip description sub-matrix \( \mathbf{BDM}_j \):
\[ \mathbf{BDM}_j = \begin{pmatrix} v^{l_j} & v^{l_j} & \cdots & v^{l_j} \\ v^{2_j} & v^{2_j} & \cdots & v^{2_j} \\ v^{3_j} & v^{3_j} & \cdots & v^{3_j} \\ v^{4_j} & v^{4_j} & \cdots & v^{4_j} \end{pmatrix} \in \mathbb{R}^{4 \times n} \]  
(6)
\( n \) is the number of rows related with band \( B_j \), 
\[
n = \begin{cases} 
2w, & f = 1 \parallel m \\
3w, & \text{else} 
\end{cases}
\]

\( BD_j \) consists of \( BDM_j \) average vector \( M_j \) and standard variance vector \( S_j \): 
\[
LBD = (M_1^T, S_1^T, M_2^T, S_2^T, \ldots, M_n^T, S_n^T)^T \in \mathbb{R}^{8n}. 
\]
Then the mean value and standard variance of the LBD are normalized respectively. In order to reduce the influence of nonlinear illumination, each LBD dimension is constrained to be less than an empirical value of 0.4. Finally, the constraint vector is re-normalized to obtain a unit LBD.

5) Matching of line segment feature descriptors. Check the LineVecs of the reference and query images, and generate candidate matching pairs based on their unary geometric attributes (the direction of LineVecs) and their local appearance similarity (measured by the distance between line descriptors). Then according to the paired geometric attributes and the appearance similarity of the candidate pairs, the consistency is calculated to obtain the matching weights, the relationship graph between the two sets of LineVecs is constructed and the matching result is established in the graph.

2.2. Feature Point Matching and Solving Camera Motion Parameters

SIFT, SURF, ORB are the more mature point feature extraction methods. SIFT feature matching algorithm is a very famous feature description and matching algorithm in the early stage. Feature extraction using SIFT operator mainly includes two steps: generating the match between feature description vector and feature description vector. SIFT features reflect the local features of the image and maintain a certain of stability for rotation, scale scaling, brightness change, angle change, affine transformation, noise. However, only a small number of features could be extracted when images with a large dip. The improvement of SIFT by SURF algorithm reduces the dimension of feature description vector and is easier to realize parallel processing. It is a robust local feature point detection and description algorithm with scale and rotation invariance, a feature operator with high accuracy and speed.

ORB uses FAST algorithm to extract feature points, and use Harris algorithm to compare the quality of FAST feature points, avoid the complex mathematical calculation as SIFT and SURF operators. Therefore, the operation speed is very fast, which can meet the requirements of real-time scene and is widely used in SLAM and pose estimation.

Because the algorithm for calculating position in line feature is not as reliable as the method in point feature and also sensitive to spatial occlusion. ORB algorithm is used in this paper to matching the image feature points and solving camera attitude between images. The process of feature point detection and camera motion calculation is as follows:

- Oriented FAST corner points detection;
- Calculating the BRIEF description operator of corner points;
- Matching the BRIEF descriptors from two images by Hamming distance;
- Filter for pairs of matched points;
- Calculating the essential matrix based on the pairs of matched points;
- Recovery of rotation and translation information from essential matrix.

Figure 3. Feature detection and camera attitude estimation.
The steps of detecting Oriented FAST corner position, calculating BRIEF descriptor according to corner position, using Hamming distance to match the BRIEF descriptor in two images are detailed in the ORB feature point matching algorithm in reference [30]. Matching point filtering is aimed at finding the minimum distance and the maximum distance between all matches, that is, the distance between the most similar and the least similar two groups of points. When the distance between descriptors is greater than twice the minimum distance, it is considered that the match is wrong. But in some cases the minimum distance is very small, could set an empirical value as the lower. According to the matching point to calculate the essence matrix, from the essence matrix to restore the rotation and translation information, this steps are detailed in the part about solving the camera motion by pole constraints from reference [31].

2.3. 3D reconstruction based on triangulation
To obtain the 3D coordinates of key points in the images, this step measured the feature points and the endpoints of the feature line segments matched in the above procedure by triangulation method. The specific theory of 3D reconstruction based on triangulation is detailed in triangulation section from reference [31].

This paper presents the following improvements to the complete algorithm:

a. In order to increase the stability of feature line segment matching algorithm, in the steps of feature line segment extraction and matching in section 2.1, three adjacent images are used in line segment descriptors and feature points extraction, and each two adjacent images are matched. The matching feature line segments and feature points are preserved and participate in the subsequent 3D reconstruction calculation, it lead to a better compare and analyze on the data of 3D reconstruction results;

b. Comparing two groups of 3D point coordinates by triangulation method, if the difference of any component in (x, y, z) coordinates larger than 5%, then a filter was set to ignore this pair of matching result and the coordinate, so as to reduce the errors from spectral registration in line matching.

2.4. Registration the reconstruction results to BIM model
Considering the scale uncertainty of line segment reconstruction, and the camera attitude estimation error of first image, priority is given to the relative position and the relative direction angle of the line segments when matching the BIM model, those direction and distance could form a word bag of vectors, a fast initialization location was obtained by combine of the word bag dictionary technology.

3. Experiment analysis
The experiment adopts the images from two positions in the basement parking lot of an office building, each of which is composed of three parallel images (the middle position is the reference image, two comparing images set two side respectively) and three forwarding images, the middle image in previous set is taken as reference images, two steps forward and take one shot for each step as comparing images, than compare the results. Because of the poor lighting environment in the basement and the obvious reflection on the ground, it is unfavorable to the measure process of visual computing, but the situation closes to the real application scene.

Reference images.
3.1. Matching of line segments in parallel motion

Because of the occlusion relationship of angle change, the results of the above two groups of experiments show that the matching accuracy is not reliable for line segments from 3 images in parallel direction. In first parallel motion experiment, algorithm find 20 matching pair of line segments and 8 of them is correct, the second experiment obtained 14 matching pair but none of them was correct.
3.2. Matching of line segments in forward direction motion

![Figure 6. The matching results of forward motion.](image)

It can be seen in figure 6, that the registration results of the three images arranged in the forward direction are relatively improved. In the two forward direction experiments, the numbers of matching line segments / the matching correct are 54/39 and 28 to /15, respectively.

3.3. Filter for high difference coordinates

This experiment has made a test of the images taken along forward direction. There were 54 successful matched line segments before filtering. Comparing the line segment coordinates by triangulation, endpoints with error less than 5% are retained. The remaining 30 pairs of line segment endpoints are shown below:

![Figure 7. The reconstruction result after the filter of coordinates.](image)
The results of the 3D segment endpoint coordinates are as follows:

### Table 1. The segment endpoint coordinates after filter

| endpoint | beginpoint | endpoint | beginpoint |
|----------|------------|----------|------------|
| x        | y          | z        | x          | y          | z        |
| -0.4492  | 0.1376     | -0.8098  | -0.66212  | -0.04929  | 0.74706  |
| 0.3778   | 0.06196    | 0.9586   | 0.24787   | 0.26293   | 0.95247  |
| 0.1075   | 0.03156    | 0.92995  | 0.10236   | 0.25002   | 0.96111  |
| 0.14568  | 0.22996    | 0.9622   | 0.34205   | 0.34818   | 0.9737   |
| 0.1483   | 0.22614    | 0.9826   | 0.35418   | 0.30713   | 0.9841   |
| 0.1493   | 0.23056    | 0.9829   | 0.28672   | 0.20418   | 0.8845   |
| 0.1496   | 0.20358    | 0.9542   | 0.26925   | 0.29228   | 0.8291   |
| 0.1496   | 0.20437    | 0.9542   | 0.26677   | 0.20418   | 0.8745   |
| 0.1494   | 0.20447    | 0.9542   | 0.26672   | 0.20418   | 0.8845   |
| 0.1494   | 0.20427    | 0.9542   | 0.26672   | 0.20418   | 0.8745   |
| 0.1494   | 0.20417    | 0.9542   | 0.26672   | 0.20418   | 0.8845   |

Comparison of 3D line segment data visualization and BIM model scene:

**Figure 8. Visualization of BIM model and the filtered segments.**

### 4. Conclusion

By experimental data, it can be seen that with the 3D reconstruction of multiple images and screening the unreliable data in the process of registration, it is feasible to initialize location of the indoor space based on the reconstruction of 3D line segment and registration with BIM model. Because of the lack of lighting in the basement environment, feature recognition is difficult, and the images distributed along parallel direction have more occlusion, the success rate of line segment matching is lower than the forward direction image. Therefore, the application of indoor initialization location based on images should try to be designed in the forward direction. The further research would be focused on the 3D line segment matching method with the goal of fast initialization location.

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### References

[1]. Harris, C., Stephens, M.: A combined corner and edge detector. In: Alvey Vision Conference. (1988)
[2]. Lowe, D.G.: Object recognition from local scale-invariant features. In: Proceedings of the International Conference on Computer Vision, Corfu (1999) 1150-1157
[3]. Lowe, D.G.: Distinctive image features from scale-invariant keypoints. International Journal of Computer Vision 60 (2004) 91-110
[4]. Raul Mur-Artal, Jose Maria Martinez Montiel, and Juan D Tardos. Orb-slam: a versatile and accurate monocular slam system. IEEE transactions on robotics, 31(5):1147–1163, 2015.
[5]. Bay, H.; Tuytelaars, T.; Van Gool, L. SURF: Speeded up robust features.?Lect. Notes Comput. Sci.?2006,?3951, 404–417.
[6]. Raul Mur-Artal and Juan D Tardós. Orb-slam2: An open-source slam system for monocular, stereo, and rgb-d cameras. IEEE Transactions on Robotics, 33(5):1255–1262, 2017.
[7]. Neira J, Ribeiro M I, Tard’os J D. Mobile robot localization and map building using monocular vision[C/OL]//5th Symposium for Intelligent Robotics Systems. 1997: 275-284. http://webdiis.unizar.es/GRPTR/pubs/NeiraSIRS1997.pdf.
[8]. Canny, J., 1986. A computational approach to edge detection. IEEE Trans. Pattern Anal. Machine Intell. 8 (4), 679–698.
[9]. Duda, R.O., Hart, P.E., 1972. Use of Hough transformation to detect lines and curves in pictures. Comm. ACM 15, 11–15.
[10]. Grompone von Gioi, R., Jakubowicz, J., Morel, J.M., Randall, G., 2008a. On straight line segment detection. J. Math. Imag. Vision 32 (3), 313–347.
[11]. Grompone von Gioi, R., Jakubowicz, J., Morel, J.M., Randall, G., 2008. LSD: A Line Segment, Technical report, Centre de Mathematiques et de leurs Applications (CMLA), Ecole Normale Superieure de Cachan (ENS-CACHAN).
[12]. Grompone von Gioi, R., Jakubowicz, J., Morel, J.M., Randall, G., 2010. LSD: a fast line segment detector with a false detection control. IEEE Trans. Pattern Anal. Machine Intell. 32 (4), 722–732.
[13]. Akinlar, C., Topal, C., 2011. EDLines: real-time line segment detection by edge drawing (ED), in: Proceedings of the International Conference on Image Processing (ICIP), September 2011, Brussels
[14]. Zhang L, Koch R. An efficient and robust line segment matching approach based on LBD descriptor and pairwise geometric consistency[J]. Journal of Visual Communication and Image Representation, 2013, 24(7): 794-805.
[15]. Liu Shasha, Zhu Qing, Tang Shengjun, etc. Building construction progress monitoring method integrating indoor 3D point cloud with BIM [J]. Geographic Information World, 2019, 26(5): 107-112.
[16]. Khashayar Asadi,; Harirahan Ramshankar2; Mojtaba Noghabe,; and Kevin Han, Real-Time Image Localization and Registration with BIM Using Perspective Alignment for Indoor Monitoring of Construction DOI: 10.1061/(ASCE)CP.1943-5487.0000847. ? 2019 American Society of Civil Engineers.
[17]. Han, K., J. Degol, and M. Golparvar-Fard. 2018. “Geometry- and appearance-based reasoning of construction progress monitoring.” J. Constr. Eng. Manage. 144 (2): 04017110. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001428.
[18]. Han, K., J. Lin, and M. Golparvar-Fard. 2015. “A formalism for utilization of autonomous vision-based systems and integrated project models for construction progress monitoring.” In Proc., 2015 Conf. on Autonomous and Robotic Construction of Infrastructure, 118–131. Ames, IA: Iowa State Univ.
[19]. Han, K. K., and M. Golparvar-Fard. 2015a. “Appearance-based material classification for monitoring of operation-level construction progress using 4D BIM and site photologs.” Autom. Constr. 53 (May): 44–57. https://doi.org/10.1016/j.autcon.2015.02.007.
[20]. Han, K. K., and M. Golparvar-Fard. 2015b. “BIM-assisted structure-from-motion for analyzing and visualizing construction progress deviations through daily site images and BIM.” In Proc., Int. Workshop on Computing in Civil Engineering, 596–603. Reston, VA: ASCE.
[21]. Han, K. K., and M. Golparvar-Fard. 2017. “Potential of big visual data and building information modeling for construction performance analytics: An exploratory study.” Autom. Constr. 73 (Jan): 184–198. https://doi.org/10.1016/j.autcon.2016.11.004.

[22]. Xu Chen, Huiqing Zhang. Research on Indoor Localization Algorithm Based on Multi-Scale Features Detection[C]. 2010 International Conference on Computational and Information Sciences. 2010, 626-629

[23]. Bilawal Mahmood, SangUk Han and Dong-Eun Lee. BIM-Based Registration and Localization of 3D Point Clouds of Indoor Scenes Using Geometric Features for Augmented Reality. Remote Sens. 2020, 12(14), 2302;

[24]. YETGIN O E,SENTURK Z,GEREK O N.A comparison of line detection methods for power line avoidance in aircrafts[C]// The 9th International Conference on Electrical and Electronics Engineering(ELECO).[S.l.]:IEEE,2015.

[25]. LIU Yang. Repeatability evaluation and precision location method of line feature for image matching[D].Changsha: Central South University,2012.

[26]. Zhang Ning, Wang Jingxue. EDLines and LSD line extraction algorithm performance exploration [J].Scientific mapping, 2020, v.45;No.270(12):120-129.

[27]. Zhang L, Koch R. An efficient and robust line segment matching approach based on LBD descriptor and pairwise geometric consistency[J]. Journal of Visual Communication and Image Representation, 2013, 24(7):794-805.

[28]. Desolneux, A., Moisan, L. & Morel, JM. Edge Detection by Helmholtz Principle. Journal of Mathematical Imaging and Vision 14, 271–284 (2001). https://doi.org/10.1023/A:1011290230196

[29]. Gioi, Rafael & Jakubowicz, Jeremie & Morel, Jean-Michel & Randall, Gregory. (2012). LSD: A line segment detector. Image Processing On Line. 2. 35-55. 10.5201/ipol.2012.gjmr-lsd.

[30]. Rublee E, Rabaud V, Konolige K, et al. ORB: An efficient alternative to SIFT or SURF[C]// International Conference on Computer Vision. IEEE, 2012.

[31]. Gao Xiang, Zhang Tao, etc. Visual SLAM 14 Lectures from Theory to Practice. Electronic Industry Press. August 2019