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PREDICTION – CORRECTION ALGORITHM USING LINE SEGMENT DETECTION

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Abstract:

Edge-drawing methods have gained increasing popularity in line segment detection due to their notable efficiency. However, existing algorithms commonly impose a pre-determined threshold on the gradient magnitude of the input image to control false positives, which could lead to the detection of line segments with insufficient completeness. To address this fundamental problem, we propose a novel method called the prediction-correction line segment detector (PCLSD). The PCLSD initiates with a prediction stage utilizing a Cannybased approach to generate line segment predictions. In the subsequent correction stage, each predicted line segment undergoes refinement. Specifically, a directional routing method is employed to extend and refit the line segment, improving the accuracy of its orientation, position, and completeness. The corrected line segment is then validated to ensure confidence. Experimental results demonstrate the superior performance of the proposed PCLSD compared to current state-of-the-art methods.

Keywords : Line segment detection, edge detection, gradient, prediction-correction

1. INTRODUCTION

Line segments convey substantial geometric and topological information in real-world scenes, making them extensively employed in diverse computer vision tasks, such as 3D reconstruction [1], simultaneous localization and mapping (SLAM) [2], pose estimation [3], vanishing point detection [4], and power line extraction from unmanned aerial vehicle images [5]. In the preceding decades, numerous line segment detectors have been introduced. Despite their apparent differences, these existing methods follow a similar set of processing steps to detect line segments. This involves initially extracting low-level features from the input image, followed by the identification of line segments based on the extracted features. The low-level image features utilized primarily include edge points .

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(bjzhong@suda.edu.cn). (a) Test Image (b) Ground Truth (c) EDLines [7] (d) ELSED [11] (e) DeepLSD [16] (f) Ours Fig. 1: Comparison of different methods in detecting lowcontrast line segments (highlighted in blue). regions [13, 14], and linelets [15]. From a more foundational gradient directions and gradient

magnitudes. Consequently, the successful detection of a line segment depends on the saliency of this segment concerning the aforementioned

two image gradient cues. In this context, a line segment is considered salient if locally computed gradient directions align well with its normal vector, and the pixels aligned in this manner exhibit relatively large gradient magnitudes, indicating high contrast. When this condition is met, a sufficient number of low-level image features can be extracted, facilitating the detection of the line segment with high completeness. Unfortunately, existing methods, especially those based on edge drawing, typically impose a predetermined threshold on the gradient magnitude to control false positives. However, this practice comes at the cost of compromising the completeness of the detected line segments. An illustrative example is depicted in Fig. 1 for demonstration. Fig. 1 (a) shows an indoor scene, in which there are three intersecting line segments between the roof and the walls, as well as between the walls.

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2. LITERATURE SURVEY

[1] Dong Wei, Yi Wan, Yongjun Zhang, Xinyi Liu, Bin Zhang, and Xiqi Wang, "ELSR: Efficient line seg ment reconstruction with planes and points guidance," in IEEE Conference on Computer Vision and Pattern Recognition, 2022, pp. 15807–15815.

Three-dimensional (3D) line segments are helpful for scene reconstruction. Most of the existing 3D-line-segmentreconstruction,

algorithms deal with two views or dozens of small-size images; while in practice there are usually hundreds or thousands of large-size images. In this paper, we propose an efficient line segment reconstruction method called ELSR 1 . ELSR exploits scene planes that

are commonly seen in city scenes and sparse 3D points that can be acquired easily from the structure-from-motion (SfM) approach. For two views, ELSR efficiently finds the local scene plane to guide the line matching and exploits sparse 3D points to accelerate and constrain the matching. To reconstruct a 3D line segment with multiple views, ELSR utilizes an efficient abstraction approach that selects representative 3D lines based on their spatial consistence. Our experiments demonstrated that ELSR had a higher accuracy and efficiency than the existing methods. Moreover, our results showed that ELSR could reconstruct 3D lines efficiently for large and comp

[2] Xin Liu, Shuhuan Wen, and Hong Zhang, "A real-time stereo visual-inertial SLAM system based on point-and line features," IEEE Transactions on Vehicular Technol ogy, vol. 72, no. 5, pp. 5747–5758, 2023.

Visual-inertial SLAM systems achieve highly accurate estimation of camera motion and 3D representation of the environment. Most of the existing methods rely on points by feature matching or direct image alignment using photo-consistency constraints. The performance of these methods usually decreases when facing low textured environments. In addition, lines are also very common in man-made environments and provide geometrical structure information of the environment. In this paper, we increase the robustness of visual-inertial
SLAM system to handle these situations by using both points and lines. Our method, implemented based on ORB-SLAM2, makes the combination of points, lines and IMU measurements in an effective way by selecting keyframes very carefully and handling the outlier lines efficiently. The cost function of bundle adjustment is formed by point, line reprojection errors and IMU residual errors. We derive the Jacobian matrices of line reprojection errors with respect to the 3D endpoints of line segments and camera motion. Loop closure detection is decided by both point and line features using the bag-of-words approach. Our method is evaluated on the public EuRoc dataset, and compared with the state-of-the-art visual-inertial fusion methods. Experimental results show that our method achieves the highest accuracy on most of testing sequences, especially in some challengeable situations such as low textured and illumination changing environments.

[3] Xinyu Lin, Yingjie Zhou, Xun Zhang, Yipeng Liu, and Ce Zhu, "Efficient and effective multi-camera pose es timation with weighted M-estimate sample consensus," in IEEE International Conference on Acoustics, Speech and Signal Processing, 2023, pp. 1–5.

Curvature scale-space (CSS) corner detectors look for curvature maxima or inflection points on planar curves. They use arc-length parameterized curvature. Therefore, they are not robust to affine transformations since the arc-length of a curve is not preserved under affine transformations. However, the affine-length of a curve is relatively invariant to affine transformations. This paper presents an improved CSS corner detector by applying the affine-length parameterized curvature to the CSS corner detection technique. A thorough robustness study has been carried out on a large database considering a wide range of affine transformations

[4] Xin Tong, Xianghua Ying, Yongjie Shi, Ruibin Wang, and Jinfa Yang, "Transformer based line segment clas sifier with image context for real-time vanishing point detection in Manhattan world," in IEEE Conference on Computer Vision and Pattern Recognition, 2022, pp. 6093–6102.

Previous works on vanishing point detection usually use geometric prior for line segment clustering. We find that image context can also contribute to accurate line classification. Based on this observation, we propose to classify line segments into three groups according to three unknown-butsought vanishing points with Manhattan world assumption, using both geometric information and image context in this work. To achieve this goal, we propose a novel Transformer based Line segment Classifier (TLC) that can group line segments in images and estimate the corresponding vanishing points. In TLC, we design a line segment descriptor to represent line segments using their positions, directions and local image contexts. Transformer based feature fusion module is used to capture global features from all line segments, which is proved to improve the classification performance significantly in our experiments. By using a network to score line segments for outlier rejection, vanishing points can be got by Singular Value Decomposition (SVD) from the classified lines. The proposed method runs at 25 fps on one NVIDIA 2080Ti card for vanishing point detection. Experimental results on synthetic and real-world datasets demonstrate that our method is superior to other state-of-the-art methods on the balance between accuracy and efficiency, while keeping stronger generalization capability when trained and evaluated on different datasets.

[5] Wenbo Zhao, Qing Dong, and Zhengli Zuo, "A method combining line detection and semantic segmentation for power line extraction from unmanned aerial vehicle im ages," Remote Sensing, vol. 14, no. 6, pp. 1367, 2022.

Power line extraction is the basic task of power line inspection with unmanned aerial vehicle (UAV) images. However, due to the complex backgrounds and limited characteristics, power line extraction from images is a difficult problem. In this paper, we construct a power line data set using UAV images and classify the data according to the image clutter (IC). A method combining line detection and semantic segmentation is used. This method is divided into three steps: First, a multi-scale LSD is used to determine power line candidate regions. Then, based on the

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object-based Markov random field (OMRF), a weighted region adjacency graph (WRAG) is constructed using the distance and angle information of line segments to capture the complex interaction between objects, which is introduced into the Gibbs joint distribution of the label field. Meanwhile, the Gaussian mixture model is utilized to form the likelihood function by taking the spectral and texture features. Finally, a Kalman filter (KF) and the least-squares method are used to realize power line pixel tracking and fitting. Experiments are carried out on test images in the data set. Compared with common power line extraction methods, the proposed algorithm shows better performance on images with different IC. This study can provide help and guidance for power line inspection

3. PROPOSED METHODOLOGY

The methods based on edge drawing performs line segment detection mainly in two steps: 1) extracting anchor points (i.e., pixels with local maximum in gradient magnitude) and 2) connecting anchor points (by a routing method) to fit line segments. Fig. 2 (a) shows the set of pixels (referred to as the candidate pixel set) obtained by imposing a predetermined threshold on the gradient magnitude, on which both of the above steps are based. It can be seen that the candidate pixel set expands as the predetermined threshold decreases, which causes the set of anchor points to expand along with it. This results in more false positives, even though the line segments detected may be more complete. Generally, line segments appear in the image areas where the gradients have a trending change, i.e., the edges. Therefore, our PCLSD extracts anchor points based on image edges rather than directly on the set of pixels where a threshold has been applied to the gradient magnitude.

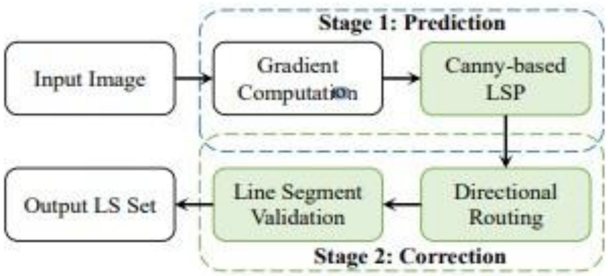

Figure 1: Proposed LIME system.

Gradient Computation :

Denote the input image as I(x, y). A small amount of Gaussian smoothing is first applied to the image I(x, y) for noise suppression. After that, the Sobel operator is used to compute the image gradient:
$\nabla I = (gx, gy)^T$, where gx and gy are the derivatives with respect to x and y, respectively. In consequence, the gradient direction can be calculated by $G\theta = \arctan(gy/gx)$, (1) and the gradient magnitude is given by $Gm = |gx| + |gy|$, (2) respectively. Note that the L1 norm is used to compute the gradient magnitude in view of its low computational expense. To facilitate the follow-up directional routing step, the gradient direction Gθ is binarized as follows: if $|gx| \geq |gy|$, then it is vertically oriented; otherwise it is horizontally oriented.

Canny-based Line Segment Prediction:

An adaptive Canny edge detector [8] is used by us to implement the line segment predictor. This edge detector not only provides edge segments consisting of nearly co-linear edge pixels, but also provides an adaptive lower limit Tm for the gradient magnitude. Note that while these edge segments are able to contain information about the line segments in the image in a more comprehensive way, they may only contain a fraction of the information about the line segments of low contrast (see Fig. 2 (c)). Lu et al. [8] perform line segment detection only on these edge segments, while we consider all the pixels that are meaningful for extracting line segments. Based on the edge segments, the line segment predictor can be easily implemented: Denote a certain edge segment as Ei . For each pixel $(x, y) \in Ei$, it is an anchor point if it is a local maxima in the gradient magnitude (within the 8- neighborhood). The set of anchor points belonging to this edge segment is a line segment prediction (in the form of a dotted line, to facilitate subsequent routing method to draw a complete line segment), denote it as Li . Then, the set of all line segment predictions is $Lp = \{Li\}_{i=1}^{N}$, where N is the number of edge segments.

Directional Routing Method :

In this work, a similar strategy to Suarez ´ et al. [11] is used to draw complete line segments. In addition, we use Tm as the threshold imposed on the gradient magnitude, which ensures that pixels belonging to low-contrast line segments are not filtered out (see Fig. 2 (b)). For each anchor points set $Li(|Li| \geq 2)$, we execute the following actions in order: • Parameterize a line segment from the anchor points. • Extend the line segment using the pixels with the following properties: 1) with maximum gradient magnitude, and $Gm \geq Tm$; 2) within a small enough distance to the line segment; 3) same orientation (horizontal or vertical) as the line segment. • Keep extending whenever possible with a depth-first strategy, i.e., adding pixels along the current direction as much as possible. When a different orientation is encountered, it creates a sibling branch in the

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search tree. When there's only one extensible pixel, the strategy falls back to the same approach as Suarez ´ et al. [11]. It is worth noting that each time a line segment is extended, the line segment needs to be reparameterized to correct information about its orientation and position.

Applications:

- 3D Reconstruction
- Simultaneous Localization and Mapping (SLAM)
- Image Analysis and Processing

Advantages:

Improved Completeness

Addresses the issue of insufficient completeness in line segment detection by utilizing an adaptive Canny edge detector.

Allows for the detection of low-contrast line segments that traditional methods may miss.

Enhanced Accuracy

Employs a directional routing method to refine the predicted line segments, improving their orientation and position accuracy.

Validates corrected line segments to ensure high confidence in the detected features.

Adaptive Thresholding

Utilizes an adaptive threshold for gradient magnitudes, reducing the risk of filtering out important low-contrast segments.

This approach contrasts with traditional methods that impose a fixed threshold, which can lead to false negatives.

Robust Performance

Experimental results demonstrate superior performance compared to state-of-the-art methods across multiple benchmark datasets. Achieves high scores in evaluation metrics such as APR, IoU, and Fscore.

Versatile Application

Suitable for various computer vision tasks, including 3D reconstruction, SLAM, and pose estimation, due to its ability to extract meaningful geometric and topological information.

Comprehensive Feature Extraction

Extracts anchor points based on image edges rather than solely on gradient magnitude, leading to a more comprehensive understanding of line segments in the image.

Post-Validation Mechanism

Implements a validation step to filter out false positives

4. EXPERIMENTAL ANALYSIS

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Figure 2: Sample Images

Figure3: Enhanced Image 1

S.No	Name	Login ID	Mobile	Email	Locality	Status	Activate
1	Test	test	9087654321	test@gmail.com	Hyd	activated	Activated
2	aleex	aleex	7854698567	aleex@gmail.com	hyd	activated	Activated
3	alex	alex	8877445588	alex@gmail.com	jhgjh	activated	Activated

Figure 4: Enhanced Image 2

Figure 5: Enhanced Image 3

Average run time comparison of our PCLSD and other comparable methods using the images from the YorkUrbanLineSegment dataset [15]. runtime of each method on the same machine equipped with Intel Core i5-11400H 2.70 GHz CPU and a NVIDIA Titan Xp GPU.

The resulting performance points, in terms of the average run times versus the average F-score, are presented in Fig. 5 (those below the lower bound are not shown). Although our method works at a slower pace, where the Cannybased line segment prediction step takes a lot of time, it is still acceptable compared to the detection performance.

5. CONCLUSION

The Prediction-Correction Line Segment Detector (PCLSD) effectively addresses the limitations of traditional line segment detection methods, particularly regarding completeness and accuracy. Existing algorithms often impose predetermined thresholds on gradient magnitudes, which can lead to the omission of low-contrast line segments. By utilizing an adaptive Canny edge detector, PCLSD enhances the detection of these segments, ensuring that important features are not overlooked. This innovative approach allows for a more comprehensive analysis of line segments in various imaging conditions.

PCLSD's two-stage methodology—comprising a prediction stage followed by a correction stage—significantly improves detection performance. The initial prediction stage generates candidate line segments, while the correction stage refines these predictions, enhancing their orientation, position, and overall completeness. Experimental results on benchmark datasets demonstrate that PCLSD outperforms state-of-the-art methods across multiple evaluation metrics, including APR, IoU, and F-score. This superior performance underscores the effectiveness of PCLSD in real-world applications, where accurate line segment detection is crucial.

Furthermore, the versatility of PCLSD makes it applicable to a wide range of computer vision tasks, such as 3D reconstruction, simultaneous localization and mapping (SLAM), and pose estimation. While the current implementation shows promising results, future work could focus on optimizing computational efficiency and exploring the integration of deep learning techniques to enhance robustness. Overall, PCLSD represents a significant advancement in line segment detection, providing a reliable and efficient solution for extracting meaningful geometric and topological information in complex visual environments.

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