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# LMFIIK: LOCAL MEDIAN FILTER INTEGRAL IMAGE KEYPOINTS

Zhezhou Yu, Ba Teer and Zhe Wang*

College of Computer Technology
Jilin University
No. 2699, Qianjin Street, Changchun 130012, P. R. China
bateer-edu@foxmail.com; *Corresponding author: wz2000@jlu.rdu.cn

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Abstract. *Effective and efficient detection of interesting features is a crucial step for various tasks in computer vision application. In this paper, a novel approach is proposed for keypoint detection and description, dubbed LMFIIK, which yields a high quality and repeatability feature that can be used to implement real-time application and resist impulse noise. LMF (Local Median Filter) that reduces time of preprocessing and maintains low computation cost and that only filters the pixels around corners that can be got by employing FAST (Features from Accelerated Segment Test) detector, not all pixels of input image, is introduced. LMFIIK is based on integral image, which enhances the reliability of corner detection. The experiment result shows that proposed feature detection algorithm achieves the best performance compared with others existing.*
**Keywords:** Computer vision, Corner detection, FAST

1. **Introduction.** Feature detection as the image preprocessing is widely used in computer vision applications, such as pedestrian recognition, object detection and face recognition. The existing feature detection algorithm has a drastic promotion in accuracy and speed. Harris-Affine and SIFT [9] for precision and robustness meet with success. Although time efficiency of PCA-SIFT improved a lot, complexity of the algorithm is too high to be used in the real-time application easily. The theory of multi-scale that was proposed by Lowe in [9] has a problem of high time complexity, which is not suitable for real-time application. Hessian matrix has a similar function to DOG while low computation cost is applied to SURF [10], yielding poor approximations of SIFT.

FAST corner detection algorithm [4] achieves desirable quality features and improves a lot in speed. However, detection effect is weakened obviously with the increasing of the impulse noise, even leading to raise the rate of errors. BRISK (Binary Robust Invariant Scalable Keypoint) algorithm [3] based on FAST detection criterion has a high operation ability, and scale invariant, while being sensitive to the noise, especially the impulse noise.

Our proposed feature builds on the well-known FAST keypoint detector and integral image theory; for this reason we call it LMFIIK (Local Median Filter Integral Image Keypoints). Both these models are attractive because of their good performance and low cost. In this paper, we address several limitations of FAST and like FAST theory, the most notable the lack of noise in FAST. Our main contributions are as follows.

- LMFIIK is robust to noise, nevertheless, FAST is sensitive to impulse noise.
- Using the integral image theory, improve the capacity of detection by our method.
- A novel idea, called Local Median Filter, is put forward, which has a huge advantage for low cost.

2. **The Research Method.** The local feature that is widely employed to system and application is a powerful tool. In geometry local features can be defined as a position information but without spatial extent. To locate features in the image, local surrounding

pixels are analyzed. The corner detection is mainly divided into three kinds of methods, detection approach based on gradient, contour detection method and template.

Harris algorithm that is based on Hessian matrix was presented by Harris et al. [12] which is one of the representatives of a gradient detection. The essence of Hessian is the gradient distribution of binary image point:

$$H(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix} \tag{1}$$

where $g(\sigma)$ (3) is a gaussian convolution kernel of scale $\sigma$. $L_{xx}(x,\sigma)$ can be defined by:

$$L_{xx}(x,\sigma) = \frac{\partial^2}{\partial x^2} g(\sigma) \otimes I(x) \tag{2}$$

where $I(x)$ is a pixel value of the point $x$ in image.

$$g(\sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{3}$$

According to Hessian matrix, a value of corner response is put into use by (4), and whether it is a corner is judged by threshold.

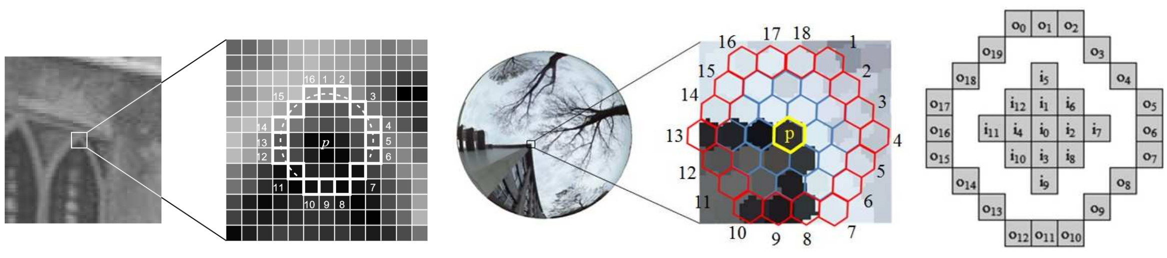
$$cornerness = \det(H) - \lambda \times trace(H) \tag{4}$$

where $\det(H)$ is the determinant and $trace(H)$ is the trace of $H$. A typical value for $\lambda$ is 0.04.

DoG (Difference of Gaussians) [9] that approximates LoG (Laplacaian of Gaussian) was proposed by Lowe, which achieved effective features of scale invariant. SIFT of high dimensionality is robust to illumination and noise, but is more expensive to compute. The family of SIFT-like algorithms were proposed in recent years. The PCA-SIFT [14] that uses the theory of principal component analysis decreases descriptor vector from 128 to 36 dimensions. As the time building descriptor rises, it annihilates the increasing speed of matching and distinctiveness.

Another type of corner detection algorithm based on contour is defined as the intersection of two lines. The main purpose of contour-based detective method which is divided into smooth curve that decreases the influence of noises and curvature evaluation that can be obtained by [8] finds maximum curvature point in the plane curve composed of edges.

The feature detection based on template can be gained by the relationship between center point and around pixels in image. SUSAN (Smallest Univalue Segment Assimilating Nucleus) [11] denotes the number of around pixels that have dramatic distance compared with center point pixel in circle mask. Recently, machine learning such as decision trees can be employed in computer vision. The nature of FAST that detects features is a relationship between 16 pixels on the circumference of circle mask and the central point in Figure 1(a). Then Rosten et al. [7] extend detection structure that increased pixels from 16 to 48, which enhanced quality but complexity of corners.



(a) (b) (c)

Figure 1. (a) is the template of circular diagram. (b) is the model structure [1] and (c) is spherical image structure.

ORB [13] that claims robust to noise is brought up on the basis of the theory that achieves the same tendency of drastic changes, which involved the candidate pixel $p$ and a set of $n$ contiguous; however, experiments show that the algorithm misjudges random value noises as corners. BRISK [3] that makes FAST corners scale invariant, nevertheless cannot detect desired features in poor quality image, which is sensitive to impulse noises. Because of ID3 (it is used in FAST) that leans toward selecting nodes that possess more samples, AGAST [6] that optimizes division trees improves quality of corners. Zhang and Hu [5] replace Hessian matrix of SURF with FAST criterion. The algorithm elevates speed but is not robust to noises.

Currently, [1] designed template structure, double-circle mask in Figure 1(b), and intricate calculation formula for detecting corner. Another successful extended approach relying on spherical image that reorganizes pixels by original image in Figure 1(c), has been put forward by Kitamura et al. [2], and the theory of FAST criterion can be used in this algorithm for detecting features.

In this paper, redesigning detection data structure, LMFIIK extracts features by integral image kernel rather than detecting pixels in image. Experiments have proved that the algorithm is robust to impulse noises in terrible quality images.

3. **LMFIIK: The Method.** In this section, we will describe LMFIIK method step by step so that the key stages of methodology can be understood.

Input form, source material that detects corners such as pixels in image, has been modified in this paper. The core idea of FAST is that the corner can be extracted, in which candidate point $p$ is brighter or darker than a set of $n$ ($n = 9$). However, three drawbacks are found about FAST. First, as it shows in Figures 2(a) and 2(b) a great distance of gray value compared with central point can be denoted by gray one, and the black one is similar to the candidate. Using FAST and detecting 16 pixels have many indeterminate factors, such as Figure 2(a); one of the uncertainties, the reason why selecting the unreasonable threshold or $s_8$ is a random value noise which leads to misjudge the corner that 8 pixels are brighter than the central point. Second, due to gray value of around pixels deciding whether candidates are corners, FAST appears edge response which detects the so-called corner is edge, rather than the corner sometimes. Third, as is well-known in Figure 2(b), the impulse noise that there exists all ambient pixels that are all brighter than the intensity of the candidate pixel or all darker, which meets a criterion of FAST corner detection, therefore, all impulse noises (salt and pepper noise and random value noise) are mistook for desired quality corners but non corners.

We design the state-of-the-art algorithm so as to overcome these shortcomings. An integral image without pixels is applied to LMFIIK that decreases the drawbacks of

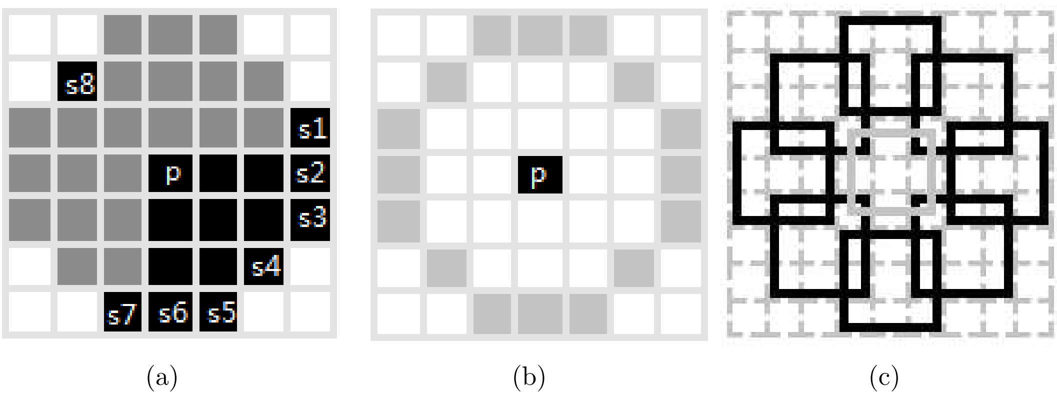



Figure 2. (a) Missed data structure of FAST algorithm, (b) data structure of impulse noise, (c) data structure of algorithm

unreasonable selected threshold or noises and increases the capacity of detection. In original image, value $p$ of the integral image is a sum of gray value from top left to $p$:

$$I(x,y) = \sum_{x'}^{x} \sum_{y'}^{y} i(x,y) \tag{5}$$

where $i(x,y)$ is gray value of the location $p(x,y)$ in original image. An integral image kernel can be defined by:

$$S(x_1,y_1,x_2,y_2) = \sum_{y=y_1}^{y=y_2} \sum_{x=x_1}^{x_2} i(x,y) = I(x_1,y_1) + I(x_2,y_2) - I(x_1,y_2) - I(x_2,y_1) \tag{6}$$

where $I(x_1,y_1)$ and $I(x_2,y_2)$ are value of top left and low right point in integral image respectively. In LMFIIK data structure, as shown in Figure 2(c), the gray rectangle is a candidate integral image kernel, and blacks are neighbors. The relationship, as shown $R_{corner}$, between gray and dark ones decides if center point $p$ of candidate integral image kernel is the corner.

$$R_{corner} = \begin{cases} 1, & C >= 5 \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where $C$ will be introduced in Formula (8). $p$ will become a corner when the value of $C$ is greater than 5.

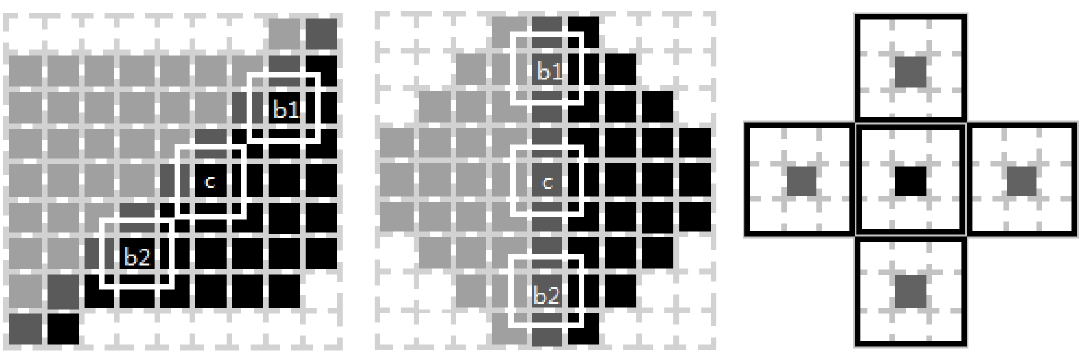
$$C = \max\left(\sum_{i=1}^{N} \tau(x_i,y_i)\%3, \sum_{i=1}^{N} 3\%\tau(x_i,y_i)\right) \tag{8}$$

where $C$ is the number of around pixels that is brighter or darker than the candidate.

$$\tau(x,y) = \begin{cases} 1, & s(x_1,y_1,x_2,y_2) - t > s(x_i,y_i,x_j,y_j) \\ 2, & s(x_1,y_1,x_2,y_2) + t < s(x_i,y_i,x_j,y_j) \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

where $\tau(x,y)$ is the relationship between around pixels and the central pixel. 1 denotes darker than the candidate and 2 is brighter than the candidate.

In order to distinguish the edge and corner whose property that extracts features is parallel, LBP (Local Binary Pattern), as shown in Figure 3(a) and Formula (9), is used in LMFIIK. The nature of distinctions between the edge and corner is whether gray value of rectangle $c$ and $b1$, $b2$ remain at the same level. The candidate is affirmed the corner when the gap of gray value between $c$ and $b1$, $b2$ is quite large, otherwise, the candidate will be deleted. LMFIIK reduces the edge response.




(a) (b)

FIGURE 3. (a) Edge response theory, (b) local median filter, black point being candidate and gray points denoting around pixels

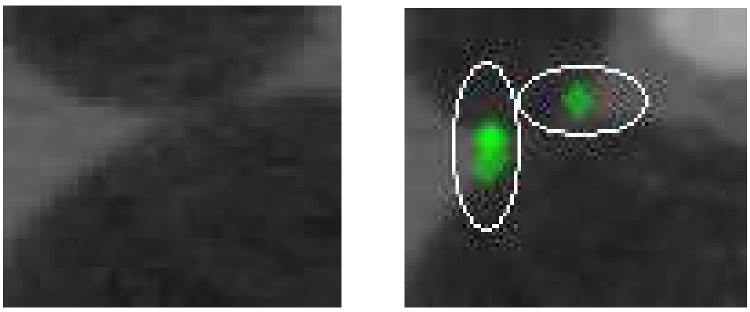
The mutual main fault of FAST and algorithms based FAST is sensitive to the impulse noise. Using median filter removes impulse noise in the original image, but loses information of the edge and corner, greatly increasing computation cost which could not be neglected. Local Median Filter (LMF) around pixels of the corner that have been detected by the algorithm are used in median filter proposed by LMFIIK. Then non corners will be deleted if the candidate is a non corner that is influenced by noises.

Firstly, so as to reduce LMF frequency, non maximum suppression can be directly applied to the corner set of R that may include non corners due to edge response and noise detected by Formula (8). Then Figure 3(b) shows that all of the candidates can be used in LMF that gray value of the point $p$ (black point) and around four pixels (gray points) of it can be replaced by median value. If gray values of three gray points are brighter or darker than the center point, it will be a true corner.

4. **Experiment.** In this section, the property of LMFIIK that resists noises is superior than other methods by experiments.

4.1. **Capacity of detection.** The detection capacity of LMFIIK improves greater than FAST. FAST just detects the 16 points nearby, whereas it is apparent that detection effect is disturbed when some of 16 points are random value noises.

One of FAST-9's faults is that anyone of 9 pixels around the candidate that predicts the non corner is influenced by the random value noise in Figure 4. Nevertheless, under the same conditions (the same threshold and scale), LMFIIK, the methodology that detects features in the integral image, is not disturbed by some noise points.



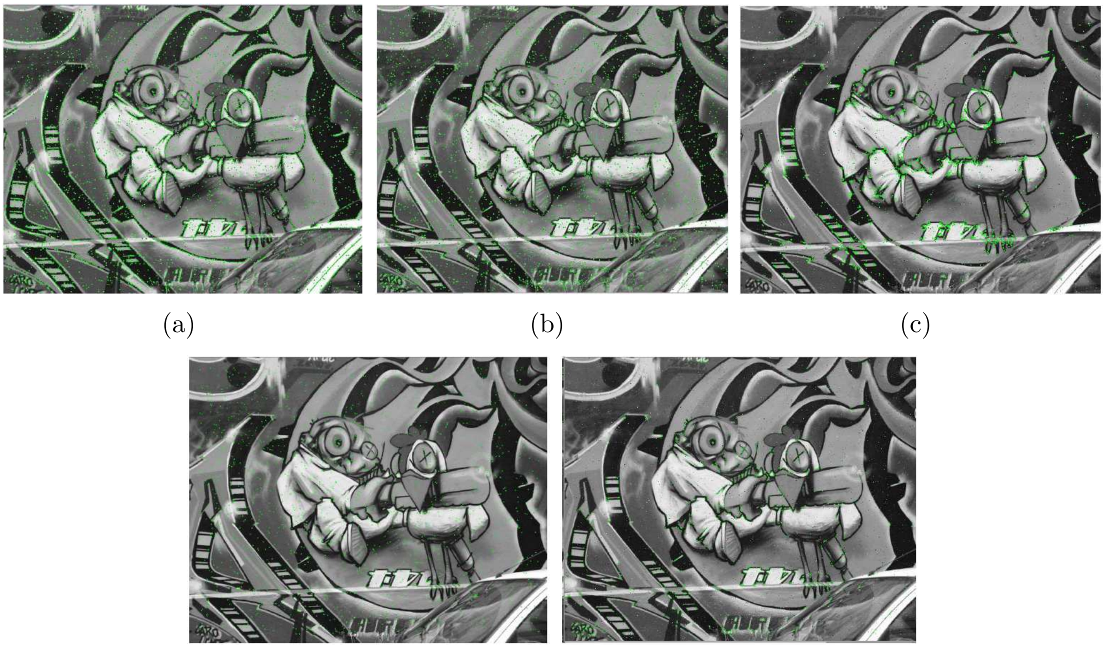
(a) An effect of FAST (b) An effect of LMFIIK

Figure 4. The effect of missing detection

4.2. **Evaluation and comparison of LMFIIK algorithm.** This section mainly includes LMFIIK comparison with other classic algorithms with experiments by OpenCV. Our proposed method has been extensively proven following the new established evaluation method and datasets in the field.

It can be obviously seen in Figure 5 that this algorithm can be greatly improved in the aspect of noise. FAST and extended algorithm BRISK and ORB will all regard impulse noises detection as the corner, thereby reducing the effectiveness of the feature. LMFIIK not only improves capacity of extracting the feature, but also is robust to the noise. In Figure 5(a), detection effect of SUSAN in the low quality image, will obviously detect corner caused by noise points.

FAST (as illuminated in Figure 5(b)) is dramatically sensitive to impulse noise, and hence almost all noises are detected by mistake. Because the ORB (shown in Figure 5(c)), and BRISK (see Figure 5(d)) based on FAST are perfected in other ways, and do not filter impulse noise, under the same conditions, detection effect would not be very ideal.



(a) (b) (c) (d) (e)

FIGURE 5. Under the same condition of scale, rotation and noise percentage, (a) is detection effect of SUSAN, (b) is corners that are detected by FAST, (c) is detection effect of ORB, (d) is detection effect of BRISK, and (e) is detection effect of LMFIIK in this paper.

Due to the application of local median filtering, LMFIIK (as shown in Figure 5(e)) will filter impulse noises that are mistakenly identified as corners, elevating the quality of the corner.

In this paper, the effective rate denoted quality of features measures degree of LMFIIK is robust to the noise. It is defined as

$$effective\_rate = \frac{c}{\bar{c} + c} \tag{10}$$

where $\bar{c}$ is the number of detecting corners that virtually are non corners caused by other factors, and $c$ is the number of true corners. According to Formula (10), the more effective rate of algorithm decreases, the more resistant the noise increases, and the better the method detects high-quality features. With the increase of pulse noise rate, the effective rate of other algorithms expect for LMFIIK fell sharply in Figure 6.

LMFIIK is proposed in the paper; as is shown above, with the increase of noise rate, the method can keep above 0.95. While for SUSAN, when image noise rate is 0.8%, effective rate will sharply decrease to 0.4. The algorithm of ORB is 0.75 when noise rate is greater than 2%. The methods of FAST and BRISK in noise rate are about 2.1%, and the corner effective rate shrinks to 0.1.

5. **Conclusion.** In this paper, we propose a novel algorithm that detects desired quality corner in poor image. LMF, a novel filter, just filters the pixels around the feature. For the direction of invariance, we apply the integral kernel to replacing the direct processing of the pixels of input image. In order to distinguish the corner and the edge point more clearly, this paper introduces the LBP algorithm that does not detect salt and pepper noises as corners mistakenly, or filtered out random value noises as corners either. Simultaneously, some flaws of LMFIIK in this paper have been optimized, and relative to other methodology based on the theory of FAST is more robust to noise.

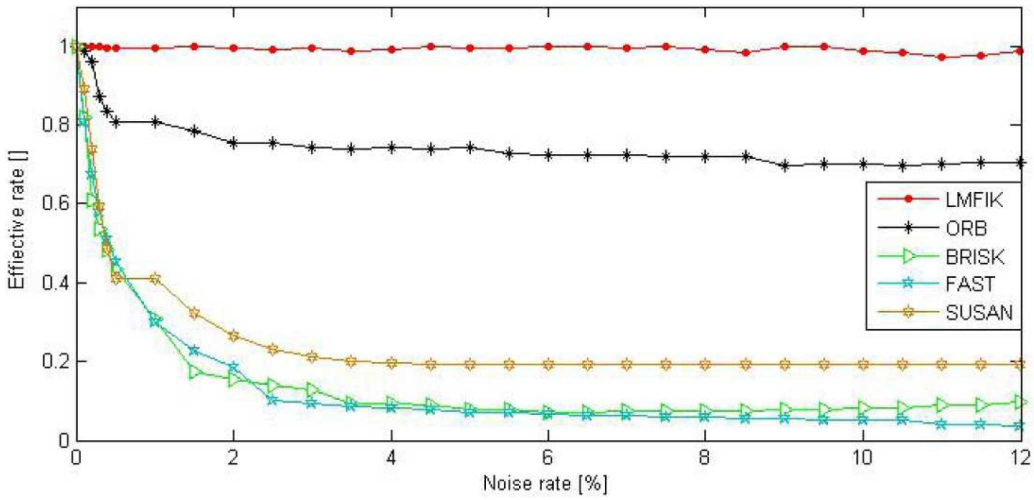



Figure 6. Comparing LMFIIK to classical methods as impulse noise rate increased

In future work, we will plan to learn more deeply, and design more advanced structures in order to achieve scale invariance. We want to combine deep learning to create faster and higher recognition algorithms. In addition, LMF is a more efficient method for image preprocessing of feature extraction, and our proposed algorithm can be employed to feature extraction, and also can be used to real-time systems.

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