Robust Corner Detector Based on Corner Candidate Region

Seungryong Kim
Dept. of Electrical and Electronic Eng.,
Yonsei University, Seoul, Korea
Email: srkim89@yonsei.ac.kr

Hunjae Yoo
Dept. of Electrical and Electronic Eng.,
Yonsei University, Seoul, Korea
Email: gnswo0112@yonsei.ac.kr

Kwanghoon Sohn
Dept. of Electrical and Electronic Eng.,
Yonsei University, Seoul, Korea
Email: khsohn@yonsei.ac.kr

***Abstract*—Corner detection is a fundamental step for many computer vision applications to detect the salient image features. Recently, FAST corner detector has been proposed to detect the high repeatable corners with efficient computational time. However, FAST is very sensitive to noise and detects too many unnecessary corners on the noise or texture region. In this paper, we propose a robust corner detector improved from FAST in terms of the localization accuracy and the computational time. First, we construct a gradient map using the Haar-wavelet response by integral image for efficiency. Second, we define a corner candidate region which has large gradient magnitude enough to be corner. Finally, we detect the corner on the corner candidate region by FAST. Experimental results show the proposed method improves localization accuracy measured by the repeatability than standard FAST and the-state-of-art methods. Moreover, the proposed method shows the best computation efficiency. Especially, the proposed method detects the corners more accurately in the image containing many texture regions and corrupted by the Gaussian noise or the impulse noise.**

I. Introduction

Corners in an image represent important information to be used for many computer vision applications such as image matching, motion detection, panorama stitching, 3-D modeling, object tracking and object recognition. Many corner detection algorithms have been proposed to detect the accurate and repeatable corners efficiently.

Harris corner detector is one of the most popular corner detectors in the early research [1]. Harris builds a structure tensor from the derivative of image with respect to direction. It is based on the Taylor expansion of the second of derivative of the local sum of squared differences (SSD). Harris defines a corner as the local maximum of the regions where two eigenvalues of the structure tensor are large. In order to overcome the computational complexity of Harris, Shi and Tomasi propose the corner measure criterion as the smallest eigenvalue of the structure tensor [2]. Smith and Brady propose Smallest Univalue Segment Assimilation Uncleus (SUSAN) method [3]. In their algorithm, the brightness similar pixels are defined as univalue segment assimilating unclues (USAN) and a corner is defined as the local minimum in USAN area. Lowe proposes Scale Invariant Feature Transforms (SIFT) [4] to detect the scale invariant feature points. SIFT builds the scale-space by convolving the Gaussian kernel with the original image and finds the local maximum at Difference of Gaussian (DoG) scale-space. SIFT detects very accurate feature point, however, the computational complexity is too high to apply to mobile applications. For computational efficiency, Bay proposed the Speeded-Up Robust Features (SURF) [5] which approximates to SIFT and outperforms other methods. Recently, Edward Rosten et al. propose the Feature from Accelerated Segment Test (FAST) [6]. It improved from SUSAN tests rapidly on a circle of candidate pixel to find corners, which meets the conditions for real-time applications.

FAST not only requires very low computation time but also represents the best localization accuracy performance. However, FAST is very sensitive to noise. Furthermore, FAST detects many unnecessary texture corners in the outdoor scene. In this paper, we propose a robust corner detector improved from FAST to address the problems of standard FAST as mentioned. We define a corner candidate region which has large gradient magnitude by evaluating Haar-wavelet response. Within the restricted corner candidate region, FAST operates to detect the repeatable corners rapidly. The proposed corner detector shows the very high localization accuracy and low computation time as compared with the standard FAST and the-state-of-art feature detectors.

This paper is organized as follows. Section 2 reviews the FAST corner detector. Section 3 introduces the robust FAST corner detector with a numerical analysis. The experimental results are presented in Section 4. Finally, Section 5 concludes the paper with some suggestions for future work.

II. The FAST Corner Detector

FAST corner detector proposed by Rosten et al. [6, 7] is derived from SUSAN corner detector. In contrast to calculating the fraction of pixels on the circular disc in the SUSAN, FAST only considers the pixels in a Bresenham circle of diameter 3.4 pixels. FAST decides a corner based on the segment test criterion that tests on the 16 pixel of a circle around a current pixel. If n contiguous pixels on the circle are brighter or darker than the intensity of the center pixel by at least t, the center pixel is classified as the corner. The computational time of FAST decreases by relaxing the segment test criterion to examine the only four compass directions around the center pixel. FAST can be improved using a machine learning approach which constructs a decision tree. FAST based on the machine learning operates in two stages. First, the each 16 pixels on the circle around pixel with respect to overall image pixels are classified into darker, similar, and brighter states. Second, the detector selects the pixel location which yields the most information determined by measurement of entropy. The recursion algorithm to construct the decision tree continues until the entropy of the each state becomes zero. In conclusion,

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the machine learning based FAST generates the decision tree that classifies all pixels as corner or not in the training set, and uses that as the decision rule of corner detection. FAST shows the most accurate and fastest corner detection result compared with the other state of the art methods.

However, FAST has several problems. First, FAST shows low performance on texture region in the image. Corners can be classified into two categories as their detected region, geometrical corner and texture corner [8]. Geometrical corners are represented on the salient region including the boundaries of the objects or intersection of edges. On the other hands, texture corners are represented on the small or textured objects in the scene. Since texture corner does not represent the physical corners of objects and need a lot of computational time, these corners are undesirable in many application. FAST only takes the comparison of pixel intensity to detect corners without considering the image structure. Thus, FAST produces many unnecessary texture corners in the outdoor scene images that specially contain many texture regions such as the natural materials, landscapes. It is a weakness of FAST to apply in outdoor environment application.

Second, FAST is sensitive to noise. The performance of FAST dramatically decreases as the amount of noise in the image increasing. FAST whose criterion is based on the pixel by pixel intensity difference extracts false corners with the high probability because the noise easily changes the intensity difference between a corner candidate pixel and its surrounding pixels. Especially, FAST may decide the impulse noise to the corner because the pixel degraded by impulse noise represents isolated intensity value. It is difficult to apply FAST corner detector to computer vision application in the present of additive noise.

Therefore, in order to increase corner detection performance, FAST has to detect the reliable geometrical corners as many as possible, rejecting the unnecessary texture corners. FAST also has to be robust in the additive noise.

III. The Robust FAST Corner Detector

In this section, we propose a robust corner detector which improves the corner detection performance of FAST while reduce the low computational time dramatically. First, we decide the regions where the gradient magnitude around current pixels is larger than the threshold to a corner candidate region. The local gradient is rapidly calculated by the Haar-wavelet response using the integral image. Given the restricted regions, we detect the corners using FAST. In our approaches, FAST can detect the high repeatable corners not for the overall region but for the reliable corner candidate region. The proposed method also reduces the corner detection computational time efficiently by rejecting the unnecessary corner.

A. Gradient Map Based on Haar-wavelet response

Corners have unique characteristic which represents strong intensity changes along both directions. The corner generally can be decided as a pixel whose gradient is the local maximum. In a similar way, we decide a corner candidate region as pixels whose local gradient magnitude is large enough to be corners. In other words, the pixels on the corner candidate region have the larger magnitude of the first-order derivative along horizontal and vertical than a certain threshold.

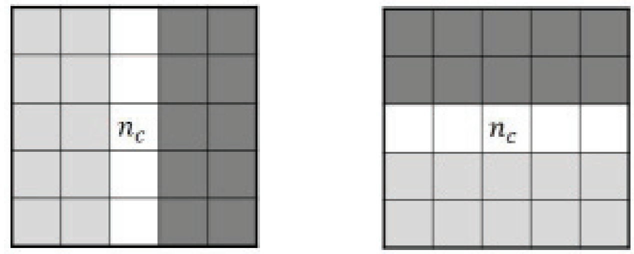


Fig. 1. Haar-wavelet windows for the Gradient computation along x-direction and y-derection

The first-order derivative can be efficiently calculated using a Haar-wavelet response. The Haar-wavelet rapidly computes the gradient with $O(1)$ computational complexity using the integral image [9]. It can compute the more accurate gradient by considering wide regions with high speed than other gradient operators such as Roberts cross-gradient operators, SOBEL operators. It calculates the difference of the sum of the particular rectangle regions. For example, two rectangle Haar-wavelet responses can be calculated as follows:

$$H(x, y) = \sum_{(s,t)\in R_1} I(s, t) - \sum_{(s,t)\in R_2} I(s, t) \tag{1}$$

where $I(s, t)$ denote the intensity of point (s, t) within the particular region R_1 and R_2. The rectangle intensity sum can be computed rapidly using the integral image. The rectangle sum calculation based on integral image only consists of some additions and subtractions of simple operator.

In order to calculate the gradient of current pixel with respect to x-direction and y-direction, we consider two fixed Haar-wavelet windows as shown in Fig. 1. We calculate the gradient along x-direction by subtracting the intensity sum of left side from the intensity sum of right side in Eq. (2). Similarly, the gradient along y-direction is calculated by subtracting the up side intensity sum from the down side intensity sum in Eq. (3). The gradient magnitude is approximated by $|dI/dx| + |dI/dy|$ instead of square roots by $\sqrt{(dI/dx)^2 + (dI/dy)^2}$ for efficiency [10]. We construct the gradient map by Haar-wavelet based the gradient magnitude.

$$\frac{dI}{dx} = \sum_{(s,t)\in R_{right}} I(s, t) - \sum_{(s,t)\in R_{left}} I(s, t) \tag{2}$$

$$\frac{dI}{dy} = \sum_{(s,t)\in R_{up}} I(s, t) - \sum_{(s,t)\in R_{down}} I(s, t) \tag{3}$$

Since the Haar-wavelet response on noise regions or texture regions represents relatively low values, it can be rejected as non-corner pixels. The Haar-wavelet response is similar to arithmetic mean filter which is a spatial filtering reducing noise effects. It approximates the arithmetic mean filter as follows:

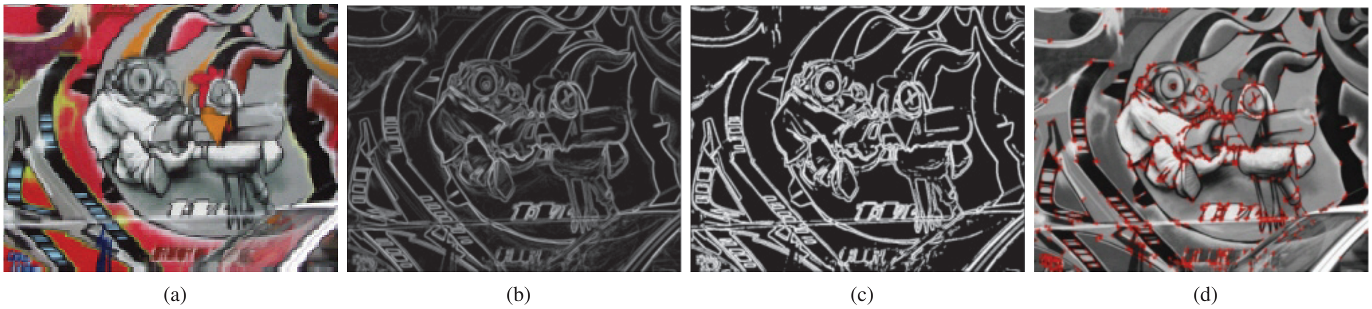


Fig. 2. Framework of the Robust Corner Detector based on Corner Candidate Region. (a) 'Graffiti' image, (b) Haar-wavelet Gradient map, (c) Corner Candidate Region, (d) corner detection results

$$f(x,y) = \sum_{(s,t)\in S_1} g(s,t) - \sum_{(s,t)\in S_2} g(s,t) = \sum_{(s,t)\in S_{xy}} \widehat{g}(s,t) \tag{4}$$

where $f(x,y)$ is the Haar-wavelet response, and $g(x,y)$ is the intensity of neighborhood at point (x,y) , and $\widehat{g}(x,y)$ is an intensity of $g(x,y)$ through the Haar-wavelet windows, and S_{xy} is the region defined by patch around center pixel. The value of the restored image $f(x,y)$ is the arithmetic mean of $\widehat{g}(x,y)$ is an intensity of $g(x,y)$ computed in the regions defined by S_{xy}. Although there exists noise in the neighborhood of (x,y), the Haar-wavelet response $f(x,y)$ represents the similar values with the response of non-noise pixels because of the effect of the arithmetic mean. It means that the Haar-wavelet response based the gradient magnitude is invariant whether the noise affects the images or not. Therefore, the robust corner detector is robust to noise effect.

B. Corner Detector Based on Corner Candidate Region

We determine the corner candidate region as sparse regions where the gradient magnitude of Haar-wavelet response exceeds the threshold. The pixel representing relatively large gradient magnitude has a high probability of being the corner. In other words, the corner candidate region means the regions where the gradient magnitude is large enough to be the corner. The gradient magnitude of pixels corrupted by the noise or unnecessary texture regions is relatively low.

The gradient map is the basis that defines the corner candidate region. For a given threshold t, the region where the gradient magnitude exceeds threshold t are determined as the corner candidate region. Otherwise, we define the region which include unreliable pixels corrupted the noise or the pixels within texture regions to the corner rejection region. As threshold t decreases, the corner candidate region widens and the number of detected corners increases. As threshold t increases, the more accurate corners are detected with the smaller detected number of corners. By using a proper threshold, we construct the corner candidate region. We divide image pixels into two regions by depending on criteria where the magnitude of gradient exceeds threshold t, 1 for corner candidates and 0 for non-corner candidates. Within the corner candidate region, we perform FAST on the limited reliable pixels defined as the corner candidate region.

Fig. 2 shows the procedure of the robust corner detector. The proposed method improves corner detection performance and decreases the computation time compared with the standard FAST. The search regions for corner detection are dramatically reduced by restricting the corner search region to on the corner candidate region, which enable the proposed method to have very fast computational time. Moreover, the proposed method detects the high repeatable corners since it does not detect the corners from unreliable regions such as noise or texture regions

IV. Experimental Results

In this section, we compare the robust corner detector with FAST and a variety of other feature detectors such as SIFT [4], SURF [5] and Harris [1] in terms of two criteria, the repeatability and computational time. The parameters of each feature detector are fixed to minimize the number of detected false corners. Especially, we also evaluate the repeatability under image degradation by the Gaussian and the impulse noise in order to verify corner detection performance of the proposed method in the present of noises. We also evaluate the computational time. We use the Mikolajczyk's database as shown in Fig. 3 in order to evaluate the repeatability under a variety of image deformation. The database consists of six image sequences and each sequence has different image deformation conditions: viewpoint change, scale change, image blur change, JPEG compression and illumination [12]. The database provides the pairs of warped image with the homography that can be used for the repeatability measurements.

The performance of corner detector in terms of localization

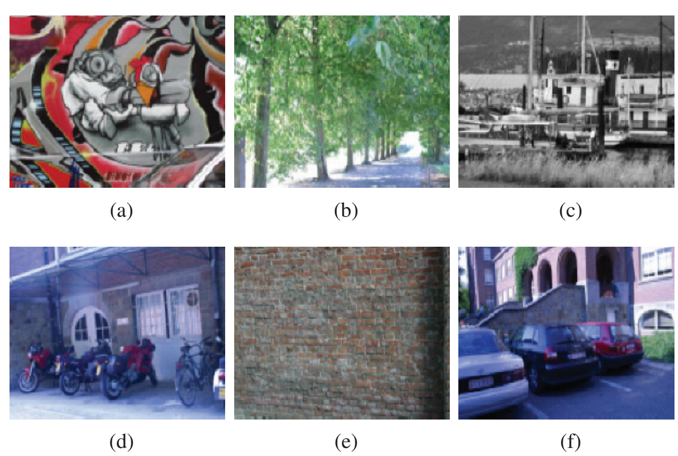


Fig. 3. Mikolajczyk's Database [11]. (a) 'Graffiti' image, (b) 'Trees' image, (c) 'Boat' image, (d) 'Bikes' image, (e) 'Wall' image, (f) 'Leuven' image

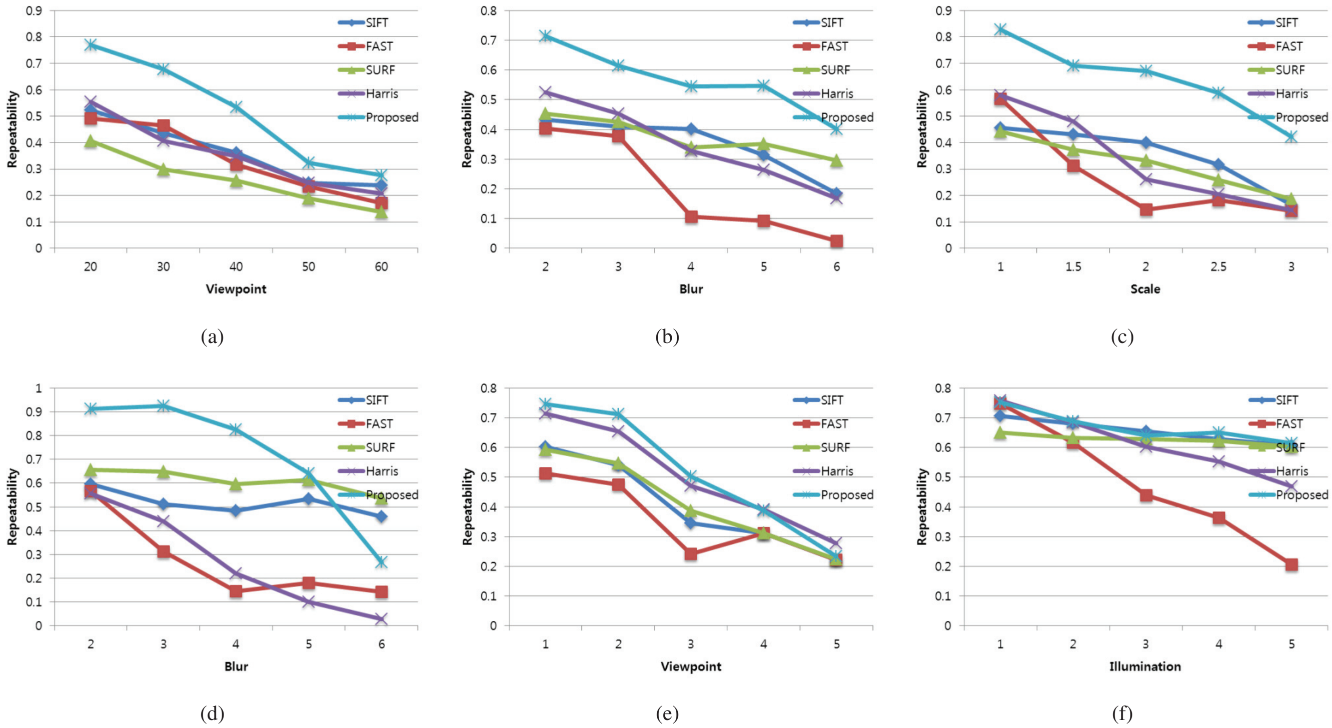


Fig. 4. Repeatability Evaluation under image deformations. (a) 'Graffiti' image, (b) 'Trees' image, (c) 'Boat' image, (d) 'Bikes' image, (e) 'Wall' image, (f) 'Leuven' image

accuracy is measured by the repeatability measurement as follows [12]:

$$r_{1,2} = \frac{C(I_1, I_2)}{mean(N_1, N_2)} \tag{5}$$

where $C(I_1, I_2)$ denotes the number of corresponding point among the corner points detected from different 2-pair image I_1 and I_2. N_1, N_2 denote the number of detected corner in each image. The repeatability is the ratio between the number of corresponding corner and the mean of the number of detected corners. The repeatability represents how accurate the detector detects the true corner.

A. Robust Corner Detector Repeatability

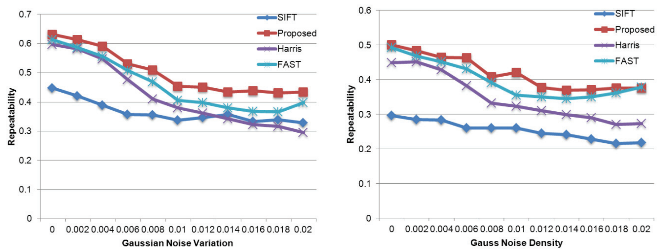
We evaluate the repeatability for the various image sequence of the Mikolajczyk database. In order to measure the detection performance for camera viewpoint changing, we use the 'Graffiti' image whose viewpoint varies and the 'Bikes' image which blur of image varies. We also evaluate the repeatability for the 'Boat' image that varies the zoom and rotations degrees. Furthermore, we test the 'Trees' image and the 'Wall' image to verify the robustness of the proposed method for the image containing many texture regions.

Fig. 4 shows that the proposed corner detector generally outperforms the other detectors. It means that the proposed method extracts more repeatable corners. Fig. 4 (a) represents the repeatability for the 'Graffiti' image, and Fig. 4 (e) represents the repeatability results for the 'Wall' image. As shown in fig. 4 (a), (e), the proposed corner detector shows better corner detection performance under the geometrical image deformation such as viewpoint change, zoom and rotation. Fig. 4 (b) represents the repeatability results for the 'Trees' image and Fig. 4 (c) shows the result of the 'Boat' image. Fig. 4 (d) represents the repeatability results for the 'Bikes' image and Fig. 4 (f) represents the repeatability results about the 'Leuven' image. As shown in fig. 4 (b), (c), (d), (f), we verify that the proposed corner detector detects the accurate true corner by rejecting the false texture corners. It means that the proposed corner detector is robust to perspective image deformation. Thus it improves the repeatability when there are many texture regions in the image.

B. Noise Robustness

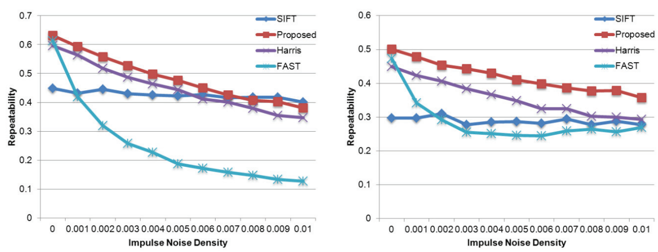
Corners can be detected around noise by conventional methods, which reduce the repeatability performance because the probability that the false corner corresponding to another false corner increases. We evaluate the repeatability for pairs of images corrupted by additive noises to verify the noise robustness of the proposed corner detector. We add the Gaussian noises and the impulse noises to the 'Graffiti' image. We evaluate the repeatability about two kinds of pair of the 'Graffiti' image. The one is that the viewpoints are 20 and 30, and the other is that the viewpoints are 20 and 40. We compare the proposed corner detector with the conventional corner detectors, known as robustness to the noise, such as Harris and SIFT. Because SIFT uses the isotropic Gaussian kernel to build the scale-space, it is highly robust to the noise [11]. Harris is also evaluated to invariance to image noise [12].

Fig. 5 represents the results for the corner detector performance in the present of the Gaussian noise. The corrupted Gaussian noise variation varies from 0 to 0.02 with zero mean which are enough to verify the noise robustness. The repeatability performance generally decreases as the amount



(a) (b)

Fig. 5. Repeatability Evaluation of the 'Graffiti' image corrupted by the Gaussian noise. (a) the viewpoint 20' and 30', (b) the viewpoint 20' and 40'



(a) (b)

Fig. 6. Repeatability Evaluation of the 'Graffiti' image corrupted by the impulse noise. (a) the viewpoint 20' and 30', (b) the viewpoint 20' and 40'

of added the Gaussian noise increases. As shown in Fig. 5 (a), (b), FAST shows a little better repeatability performance than the Harris and SIFT. The proposed corner detector shows the best performance among other corner detectors. This means that the proposed FAST invariantly detects the true corners on the Gaussian noise deformation.

Fig. 6 (a), (b) represent the results for evaluation of the detection performance in the image corrupted by impulse noise. Most corner detectors known as being robust to noise are vulnerable to the presence of impulse noise because it is difficult to estimate parameters and to expect the pattern. FAST decides the impulse noise pixels to the corner because they do not consider whether the pixels are false corners or not. In order to verify robustness to impulse noise, we evaluate the repeatability for images corrupted only by the impulse noise whose density varies from 0 to 0.01. As expected, the repeatability measurement as the impulse noise density increasing rapidly drops on FAST. The Harris shows that the repeatability decreases more gradually than FAST. However, the proposed corner detector shows the better performance than Harris, which means the proposed corner detector is more robust to image noise than other detectors. On the other hand, SIFT is invariant to noise, even overcoming the performance of the other detectors in the high noise density. However, SIFT has the serious weakness that computation time is too high. Therefore, we conclude the proposed corner detector is very efficient to the image noise.

C. Computational Time Performance

The computational time of FAST has already been compared to a variety of corner detectors in [7]. It is verified that FAST is faster than other state of the art corner detectors. In order to evaluate the time performance, we compare the

TABLE I. COMPUTATIONAL TIME EVALUTION RESULTS

Algorithm	*Proposed*	*FAST*	*SURF*	*SIFT*
Computation Time (s)	0.1701	0.8397	1.2184	5.5029

computational time of the proposed corner detector with that of the FAST, SUSAN and SIFT. Since the proposed method limits the corner search area to the narrow candidate regions, the computation time to detect corners is dramatically reduced. The experiments are run on Intel(R) Core(TM) 2 Quad CPU Q6600 at 2.40 GHz and the algorithms were implemented by using Matlab7. We evaluate 10 images fixed as 256 by 256 sizes. Table 1 shows that the proposed corner detection algorithms are faster than the conventional FAST nearly 5 times. The experimental results show that the proposed corner detector is the fastest among the state of the art corner detectors.

D. Corner Detection Results

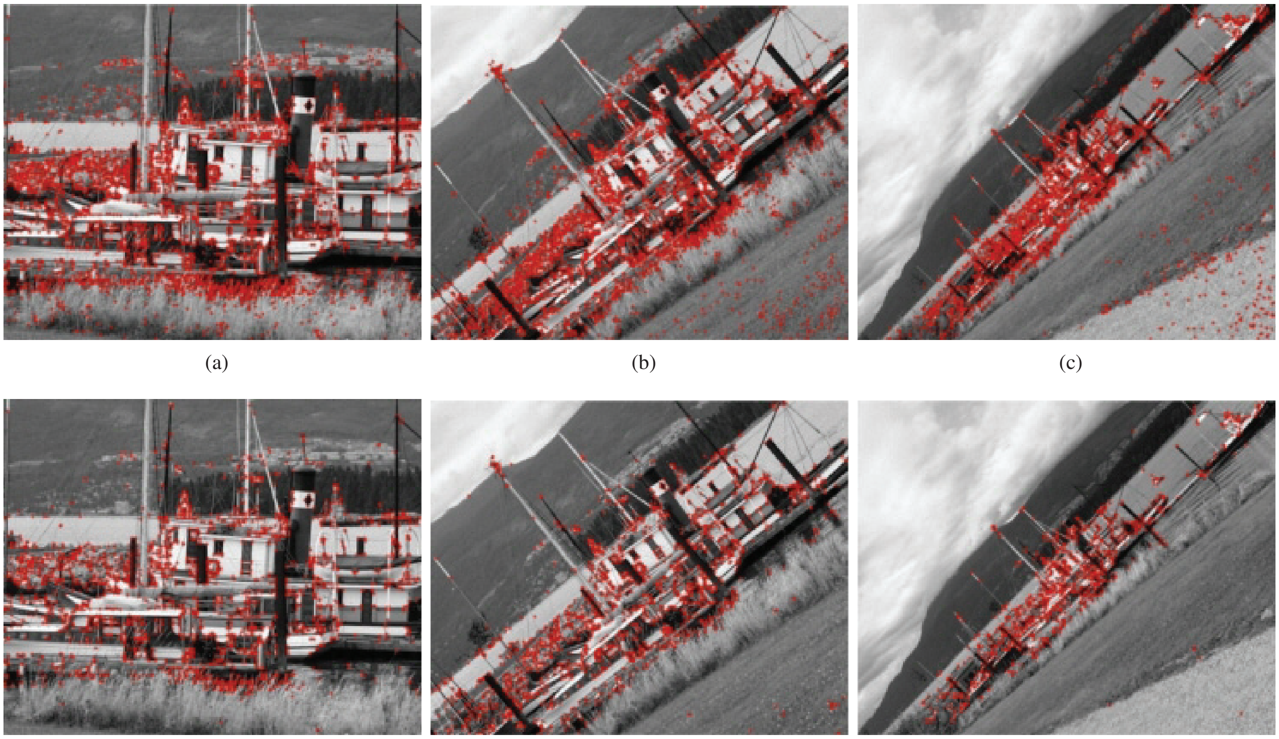
Fig. 7 shows the corner points detected by FAST and the proposed corner detector for the 'Boat' image which has many texture regions. In the results of FAST, too many unnecessary corner points are detected on the texture regions such as in the grass, landscape, which have difficulty in analyzing image contents accurately. However, the corners detected by the proposed corner detector are concentrated on the salient information in the image. The corners detected by the proposed corner detector precisely describe the 'Boat' contents better than those detected by FAST.

Fig. 8 shows the detected corners for the 'Graffiti' image distorted by the impulse noise density 0.005. Fig. 8 (a), (b), (c) represent corners detected by FAST, and Fig. 8 (d), (e), (f) represent corners detected by the proposed corner detector. FAST detects too many corners on the overall image because they mistakenly decide the impulse noises to the corner. The corners detected by FAST cannot provide the image contents information accurately. However, the proposed corner detector detects the true corners on the proper corner positions. In other words, the corners detected by the proposed corner detector can indicate the interest contents of images with invariant to noise.

V. CONCLUSION

In this paper, we propose the robust corner detector improved from FAST. First, we construct the gradient map of pixel using Haar-wavelet response based on integral image. Second, we define the corner candidate region as pixels which have the large gradient magnitude. Finally, FAST rapidly operates on the restricted corner candidate region. The experimental results show the proposed method improves localization accuracy measured by the repeatability than FAST. Especially, when the image is corrupted by the Gaussian noise or the impulse noise, the proposed corner detector shows better repeatability performance than FAST and the other corner detectors. Moreover, the proposed method shows the fastest computation time among the state of the art corner detectors.

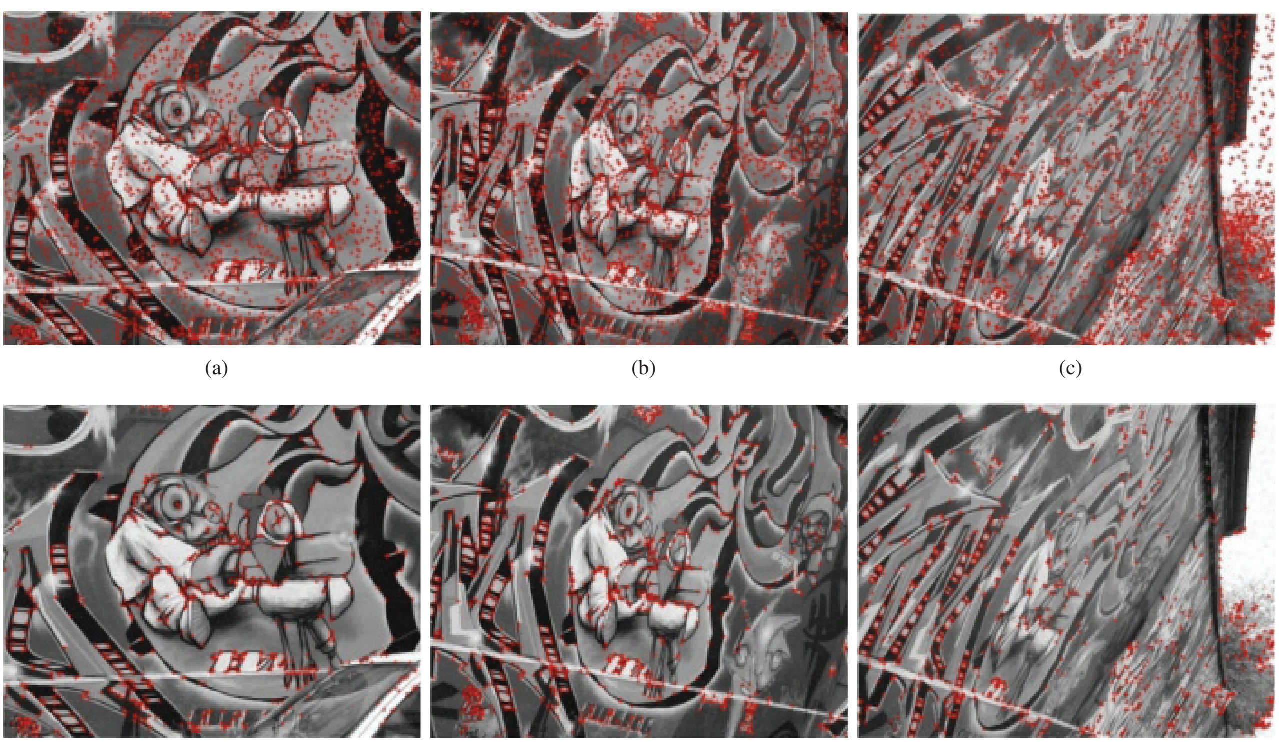
The corner candidate region approach can be applied not only to FAST but also to other corner detectors. The proposed corner detector performance, however, depends on the initial corner candidate regions sensitively. The threshold of the gradient magnitude has to be properly determined to define



(a) (b) (c)

(d) (e) (f)

Fig. 7. Detected corners for the 'Boat' image containing texture regions by the FAST and the proposed corner detector. (a)-(c) Corners detected by the FAST, (d)-(f) Corners detected by the Proposed Method



(a) (b) (c)

(d) (e) (f)

Fig. 8. Detected corners for the impulse noise added 'Graffiti' image by the FAST and the proposed corner detector. (a)-(c) Corners detected by the FAST, (d)-(f) Corners detected by the Proposed Method

the reliable corner candidate region. Moreover, we have to choose the proper Haar-wavelet window size to yield high robustness. For the further research, we will extend the robust corner detector to the color domain. We will also extend the robust corner detector to scale invariant corner detector.

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