A Modified RANSAC Based Method for Extracting Primitive Shapes from Image

Yingdi XIE † Jun OHYA ‡

† Student of GITS, Waseda University A201, Nishitomida Okuboyama 1011, Honjo, Saitama, 367-0032 Japan

‡ Faculty of GITS, Waseda University A201, Nishitomida Okuboyama 1011, Honjo, Saitama, 367-0032 Japan

E-mail: † xieyingdi@ruri.waseda.jp, ‡ ohya@waseda.jp

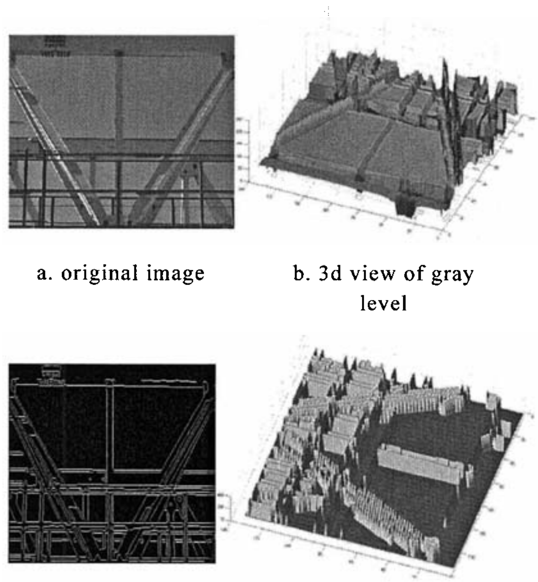
Abstract Primitive shapes extraction in image processing, such as line and circle, is of fundamentally importance. In this paper, we propose a modified ransac based shape detection method. Through a repetitive process that randomly selecting points and validity evaluation, feature models could be successfully obtained. In the experimental results, the effectiveness of this method is demonstrated.

Keyword low-level feature detection, modified RANSAC

1. Introduction

In computer vision research, all features in images can be coarsely classified into low-level features and high-level features. Low-level features can be extracted directly from the original images, whereas high-level feature extraction must be based on low-level features. Therefore, low-level features are important and critical components in a scene understanding system, the result of the extraction being the basis of the high level processes. Typical low-level features include edges [1](Fig.1), corners [2], and (to a lesser extent) ridges [3]. However, instead of raw features, semantic explanation, such as shape description is more desirable. In this paper, we will focus on the development of shape extraction.

Among various shapes, the issue of line detection has the longest history of research. In the previous literatures on this issue, the methods could be broadly classified into four categories [4], statistical based [5], gradient based [6][7], pixel connectivity-edge linking based [8] and Hough transform (HT) based models [9]. The method mentioned in [5] is a hypothesize test algorithm to extract line segments of specified lengths by hypothesizing their existence by the use of local information. In their attempt, the statistical properties of a digital model of an ideal segment were explored to verify the hypothesis and thus, it is generally classified as a statistical based approach. Contrary to this statistical based approach, an approach which explores gradient magnitude and orientation properties of each pixel for the purpose of detecting line segments in an image was originated in [6]. The principle of this approach is to utilize the gradient orientation to segment the image into a set of homogeneous regions. The work of [6] was further improvised by [7]. However, the algorithm proposed in [7] fails to identify even linear edges sometimes, if they happen to be parts of curve segments.



a. original image   b. 3d view of gray level

c. edge image by canny   d. 3d view of edge image

Figure 1. Edge feature of an image.

Algorithms based on the idea of finding out local edge pixels, linking of the found pixels into contours on the basis of proximity and orientation, and then segmenting the contours into relatively straight line pieces were also proposed. The method proposed by Nevatia and Babu [8] is a pixel connectivity-edge linking algorithm widely used in several applications which involve extraction of continuous line segments. The main advantage of pixel connectivity-edge linking algorithms is that the connectivity among all the pixels which are identified as linear edge pixels is very much ensured. Because of this fact, these methods are indeed said to outperform other line detection methods. On the other hand, a family of line detection algorithms based on Hough transform has been proposed. The original Hough transform technique implemented by Duda and Hart is nowadays called standard Hough transform (SHT). Despite the fact that the SHT endures noise and discontinuities in an image, it has some inherent limitations such as high computing time, unwieldy memory requirement, low peaks for short lines and incapability in preserving edge pixel connectivity. These inherent limitations have restricted the usage of the Hough transform technique to only images of smaller size.

In order to enhance the applicability of the SHT to various domains, several improved versions, including Fast HT, Adaptive HT, Combinatorial HT, Hierarchical HT and Multi-resolution HT were proposed. In all these improved techniques, the complexity involved in the process of deciding local peaks is reduced. However, these models still require a complete scan of the entire image for pixel transformation and each pixel has got to be considered in all orientations. Moreover, the performance of HT family can be compromised due to the discrete nature of the image. Approximations are made to the true angle of a line, as digitally it will be represented by many short segments. It therefore becomes more difficult to extract the true angle from parameter space.

It is evident from the above discussion that the researchers have been attempting to develop more efficient as well as effective techniques for extracting linear segments from an image. However, no single and robust solution that is of effectiveness as well as efficiency and robustness is explored.

With this backdrop, a novel and robust approach, which improves the trade-off between computational cost and robustness is presented in this paper. Moreover, the proposed algorithm is capable of identifying not only lines, but also other low-level features by specifying corresponding models. In the next section, general framework of the proposed method is presented. The detail of processing steps is described in section 3 and 4. In section 5, experimental results are demonstrated. Conclusion and discussion of this method is given in section 6.

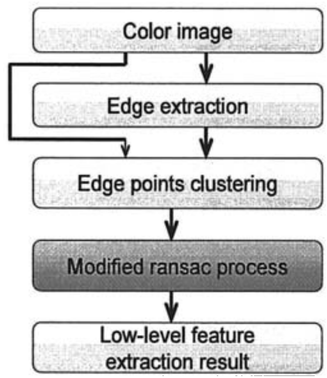


Figure 2. Block diagram of this method.

2. General framework

As demonstrated in Fig. 2, our proposal for low-level feature extraction procedures includes the following steps: (1) Edge extraction; (2) Edge points' clustering; (3) Modified ransac process. In this work, canny operator is utilized to generate edge image. In order to decrease false low-level feature extraction, the edge points are then clustered against the colors of the original image and their corresponding gradient information. The detail of the clustering procedure is described in section 4. The grouped edge points are processed according to clustering result, by a modified ransac procedure. In this step, multiple low level features could be generated with the elimination of the noise points. The details are described in section 3. In section 5, experiment results for line extraction are illustrated.

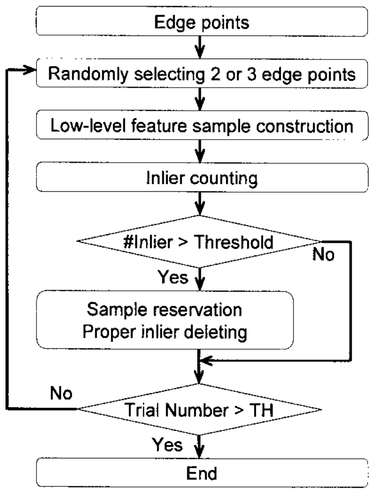


Figure 3. The computational logic of modified ransac for low-level feature detection

3 Modified ransac

In the previous work [10], a modified ransac strategy to extract multiple samples of a model under a noisy environment is introduced. The logical flow of the modified ransac is indicated by the following steps

(1) Randomly select a minimum data set S_I, required to compute a required model from the universal set, denoted as I.

(2) Compute a model M_I with set S_I. Suppose that the, "proper inlier" and "Quasi-inlier" are the data whose distance to the computed model M_I is less than a predefined threshold TH_1 and TH_2 respectively, where $TH_1 < TH_2$. Compute the proper inlier and quasi-inlier for all data within I. Count their numbers. Let the number of proper inlier as $N_{th1,I}$, quasi-inlier be $N_{th2,I}$ respectively. Notice, both proper inlier and quasi-inlier are treated as the inliers to M_I.

(3) If the inlier number is larger than the predefined threshold TH_3 for validating the effectiveness of the computed model M_I,

$$N_{th1,I} + N_{th2,I} > TH_3 \quad (1)$$

label the proper inliers with M_I and "proper" mark. The quasi-inliers are labeled with M_I and "quasi" mark. Update the universal data set I by deleting the proper inliers.

(4) Repeat step 2 and 3 until no valid model satisfying Eq. 1 can be found in a certain times of trial for the universal set I, which keeps being updated. For the quasi-inliers, when compete occurs for their assignment to different labeling, treat them as the inliers of the model with smaller distance.

From above description, the above procedures reserve all desirable samples of a model in a noisy environment. Low-level features' extraction with the modified ransac processes according to the following steps. As demonstrated in Fig. 3, we randomly select minimal pixels that required constructing a sample of a certain low-level feature, for instance 2 points for line, three points for circle. A feature sample is constructed, and its validity is verified through counting the inlier number for all the edge pixels. The valid sample is recorded. Its corresponding proper inliers are labeled and then deleted from the edge points. Repeat the above step until the edge points are empty or the trial number meets pre-defined threshold.

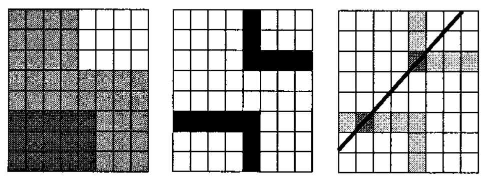


Figure 4. Left: Original image. Middle: Edge pixels which are labeled in black. Right: Example of wrong selection to build a line sample.

4. Edge pixel clustering

With the modified ransac logic, we could successfully extract multiple low-level feature samples within noisy images. However, experiment shows that, processing with the raw data of edge pixels will generate redundant samples at a certain possibility. Moreover, the computational efficiency varies significantly according to the noise factor. As for the first defect, an example is shown in Fig. 4. Accordingly, we cluster the original edge points before modified ransac process. Weights and

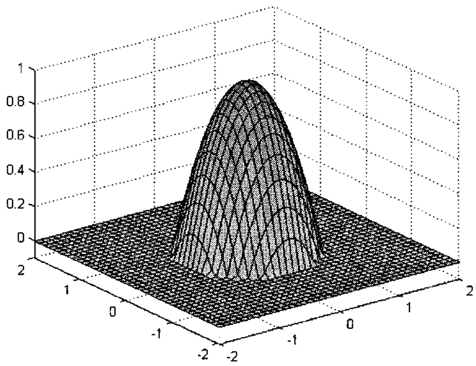


Figure 5. Epanechnikov Kernel function image for two dimensional feature space.

clustering result are assigned labeled to each edge point. Then, for each cluster the modified ransac process select points by a Gaussian sample with respect to the weights.

In this paper, we adopt mean shift [11] to cluster the edge points. The clustering procedure of mean shift is as follows:

(1) Choose a search window size.
(2) Choose the initial location of the search window.
(3) Compute the mean location (centroid of the data) in the search window.
(4) Center the search window at the mean location computed in Step 3.
(5) Repeat Steps 3 and 4 until convergence.

In the low-level feature detection, the computation of mean shift is implemented in a nine dimensional feature space, which composes of $(S_x, S_y, r, g, b, r_\nabla, g_\nabla, b_\nabla, grad)$, where, (r,g,b) represents the color of the target edge pixel, $(r_\nabla, g_\nabla, b_\nabla)$ is the color of a target pixel's neighbor in its gradient orientation, $grad_p$ is the gradient orientation. Then, the clustering procedure runs as the following steps:

(1) Initially define the bandwidth for spatial position, color and the gradient orientation. Randomly select a point in the predefined feature space.
(2) Compute the new centroid by Eq.2. The centroid update function is designed by concerning the independency of pixel position, color information and gradient orientation, as denoted as follows:

$$x = \Big[\underbrace{S_x S_y}_{x_s}\ \underbrace{r\ g\ b\ r_\nabla\ g_\nabla b_\nabla}_{x_{rgb}}\ \underset{x_{grad}}{\underset{\downarrow}{grad}}\Big]$$

Then the update function is given by:

$$M(x) = \frac{\sum_{i=1}^{n} x_i G_s G_{rgb} G_{grad}}{\sum_{i=1}^{n} G_s G_{rgb} G_{grad}} \tag{2}$$

where, $$G_s = g_s\left(\frac{\left\|x_s - x_{is}\right\|^2}{h_s^{\,2}}\right) \tag{3}$$

$$G_{rgb} = g_{rgb}\left(\frac{\left\|x_{rgb} - x_{irgb}\right\|^2}{h_{rgb}^{\,2}}\right) \tag{4}$$

$$G_{grad} = g_{grad}\left(\frac{\left\|x_{grad} - x_{igrad}\right\|^2}{h_{grad}^{\,2}}\right) \tag{5}$$

where, the kernel function we adopt for each of the above equation is Epanechnikov Kernel:

$$g_s(t) = \begin{cases} 1 - t^2 & |t| \le 1 \\ 0 & else \end{cases} \tag{6}$$

whose typical image for two dimensional computation is demonstrated as Fig.5.

(3) Move the starting point to the current centroid.
(4) Repeat the above steps until the centroid converges.
(5) Cluster the points whose corresponding points in feature space are involved in the above computation.

In Fig.6, the left is the gradient map for edge points demonstrated in Fig.4, the right figure is a clustering result example. Fig.7 demonstrates the processing result for real edge image.

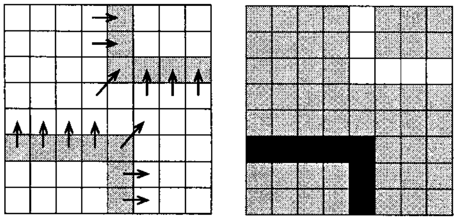
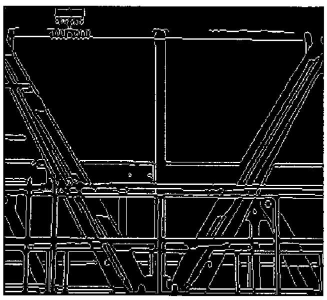
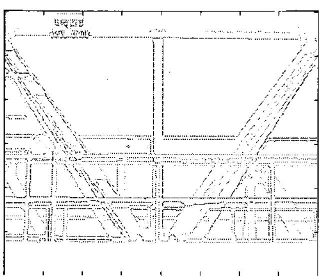


Figure 6. Left: gradient map for edge points. Right: clustering result example.

After clustering, each edge point is labeled with a cluster index, and a weight which is the Euclidean distance from the point to the clustering centroid in feature space. Then, in stead of all the edge points, the modified ransac procedure starts with selecting points only from the same cluster with small weights. Therefore, the modified ransac becomes much more effective and efficient.



a. edge image by canny



b. Clustering Result for edge points

Figure 7. a. Edge extraction example by canny operator for the image of Fig.1 (1); b. Clustering result by mean shift.

5. Experimental results

The experiments are carried out by assigning the parameters in mean shift clustering and modified ransack as the following table. The experimental results that demonstrated in Fig.8 demonstrate the effectiveness of this algorithm.

Parameters		Value
Mean Shift	Spatial position bandwidth h_s in Eq.3	80
	color bandwidth h_{rgb} in Eq.4	100
	gradient orientation bandwidth h_{grad} in Eq.5	2
Modified ransac	Quasi-inlier threshold	0.75
	Proper-inlier threshold	0.5
	Validity threshold	50

Table 1. Parameter settings for the experiment

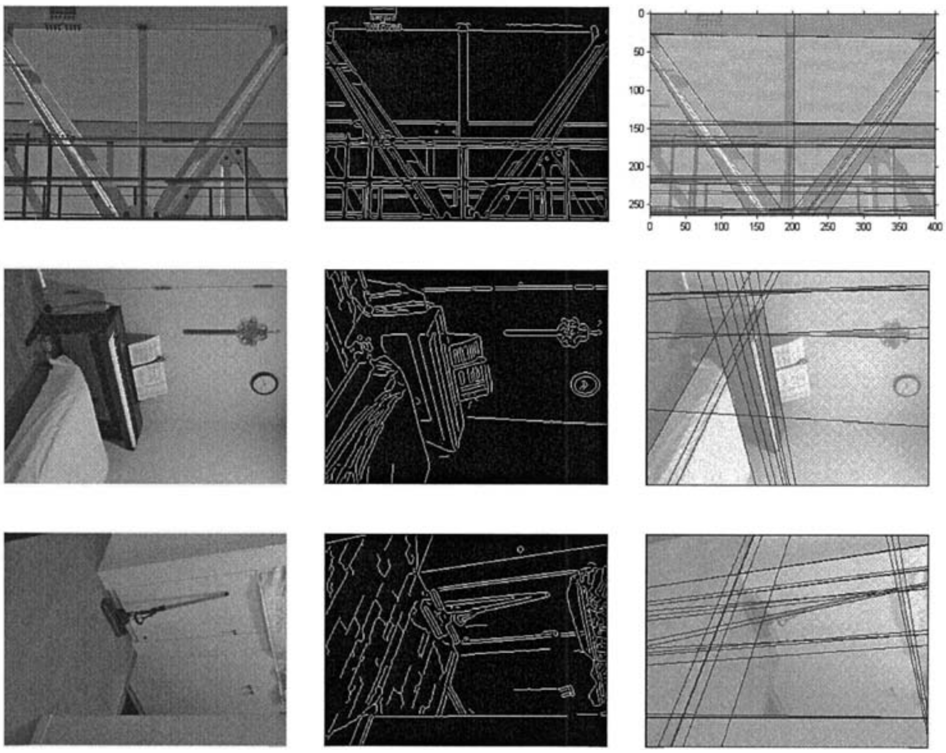
6. Discussion and conclusion

Detection of lines and other low-level features from an image for its recognition is an important stage in computer vision applications. In this paper, we proposed a modified ransac based line detection method. In the experimental results, the effectiveness is demonstrated. On the other hand, for the intrinsic characteristic of modified ransac, this method could also be applied to extract other low-level features, such as circle. It could be achieved by simply substituting the corresponding functions of specified other low-level features to the model computation procedure in modified ransac. The proposed method is simple to realize and robust to noise. It has the capability to extend to extraction of other low-level features.

References

[1] J. Canny, "A Computational Approach to Edge Detection", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol 8, No. 6, Nov 1986.

[2] C. J. Harris and M. Stephens. "A combined corner and edge detector." Proc. 4th Alvey Vision Conferences, pages 147-- 151, 1988.



a b c

Figure 8. Experimental results. Column a. Original images. b. Edge images. c. Line extraction results.

[3] R. Carmona, W. L. Hwang, B. Torr'esani, "Multiridge Detection and TimeFrequency Reconstruction," IEEE Trans. on Signal Processing, vol. 47, no. 2, February 1999.

[4] D. S. Guru, B. H. Shekar and P. Nagabhushan, “A simple and robust line detection algorithm based on small eigenvalue analysis”, Pattern Recognition Letters,Vol. 25, Issue 1, 5 Jan 2004, pp. 1-13

[5] Mansouri, A., Malowany, S., Levine, M.D., 1987. Line detection in digital pictures: A hypothesis prediction/verification paradigm. Comput. Vision Graphics Image Process. 40, 95 - 114

[6] Burns, J.B., Hanson, A.R., Riseman, E.M., 1986. Extracting straight lines. IEEE Trans. Pattern Anal. Machine Intell. 8 (4), 425 - 455.

[7] Nelson, R.C., 1994. Finding line segments by stick growing. IEEE Trans. Pattern Anal. Machine Intell. 16 (5), 519 - 523.

[8] Nevatia, R., Babu, K.R., 1980. Linear feature extraction and description. Comput. Vision Graphics Image Process. 13, 257–269.

[9] Duda, R.O., Hart, P.E., 1972. Use of Hough transformation to detect lines and curves in pictures. Commun. ACM 15 (1), 11–15.

[10] Yingdi Xie, Jun Ohya, "A Modified RANSAC mechanism: Multiple models extraction algorithm", IPSJ SIG-CVIM: Computer Vision and Image Media, Vol.2006, No.93, pp. 159-166, Sep.2006

[11] Comaniciu D, Meer P. Mean shift: A robust approach toward feature space analysis. IEEE Trans. on Pattern Analysis and Machine. Intelligence, 2002,24(5):603–619.