

An Efficient Color Edge Detection Using the Mahalanobis Distance

Kittiya Khongkraphan*

Abstract—The performance of edge detection often relies on its ability to correctly determine the dissimilarities of connected pixels. For grayscale images, the dissimilarity of two pixels is estimated by a scalar difference of their intensities and for color images, this is done by using the vector difference (color distance) of the three-color components. The Euclidean distance in the RGB color space typically measures a color distance. However, the RGB space is not suitable for edge detection since its color components do not coincide with the information human perception uses to separate objects from backgrounds. In this paper, we propose a novel method for color edge detection by taking advantage of the HSV color space and the Mahalanobis distance. The HSV space models colors in a manner similar to human perception. The Mahalanobis distance independently considers the hue, saturation, and lightness and gives them different degrees of contribution for the measurement of color distances. Therefore, our method is robust against the change of lightness as compared to previous approaches. Furthermore, we will introduce a noise-resistant technique for determining image gradients. Various experiments on simulated and real-world images show that our approach outperforms several existing methods, especially when the images vary in lightness or are corrupted by noise.

Keywords—Color Image, Edge Detection, Mahalanobis Distance

1. INTRODUCTION

Edge detection is one of the most important tasks in image processing and computer vision because it filters out irrelevant information while maintaining the important structures of objects in an image. Accurate edge detection may lead to the increased performance of subsequent operations, such as object detection, object recognition, and object tracking.

Typically, edge detection is performed on grayscale images when the edges are defined as discontinuities or when there are sudden changes in pixel intensity. These changes characterize some boundaries in the images. For color images, the same technique may be applied after the images are converted to grayscale. However, this approach may fail to detect any edges in color images that are characterized by the change in pixel hue but not pixel intensity. In fact, Novak and Shafer [1] reported that grayscale edge detection techniques can only account for 90% of the edge points in color images, while the remaining 10% require the usage of some color edge detection techniques.

※ This work was supported by the Pattani Campus Research Fund from Prince of Songkla University in Thailand.

Manuscript received September 16, 2013; accepted February 5, 2014.

Corresponding Author: Kittiya Khongkraphan (ykittiya@bunga.pn.psu.ac.th)

* Department of Mathematics and Computer Science, Faculty of Science and Technology, Prince of Songkla University, Pattani Campus, Thailand, 94000. (ykittiya@bunga.pn.psu.ac.th)

Although many approaches have been proposed to detect edges in color images, the problem of color edge detection is still very challenging since it is difficult to extract edges from several components of a pixel (color vector) in color images. The two major approaches for color edge detection techniques are monochromatic-based and vector-based approaches [2].

The monochromatic-based approach is extended from the grayscale edge detection techniques. In this approach, gradient operators are applied to each color channel separately and the resulting edge detections are combined using some methods, such as summation [3,4], and a disjunction logical operator [5] to produce the final edge detection result. The monochromatic-based techniques often produce false or missed edges because they fail to consider the correlation among color channels.

The vector-based approach employs the various features of the 3-dimensional space for edge detection in color images. This approach can extract more information from the color images because it considers the vector nature of color images by not decoupling their color components. The techniques in this approach often offer better results than the traditional grayscale edge detection techniques [2], such as with the monochromatic-based approach.

The main contribution of our paper is the introduction of efficient vector-based edge detection for RGB color images. Our proposed method considers the nature of colors as color components are correlated. The key idea is to efficiently measure a color distance using a statistical distance, such as the Mahalanobis distance, which allows us to consider the hue, saturation, and lightness separately. This method is robust against the change of lightness as compared to previous methods that employ the Euclidean distance in measuring color distances [6-12]. Additionally, we propose a new technique to reduce the errors that are due to high frequencies of noisy pixels. This technique employs the information from connected-neighbor pixels to determine image gradients instead of blurring images or rejecting outlier pixels. This method can accurately define both the gradient magnitude and gradient direction without eliminating the details of the image.

This paper is organized as follows: after this initial introduction, Section 1 continues with the presentation of previous approaches for vector-based color edge detection. The Mahalanobis distance is also presented in this section. Our proposed method is described in Section 2. In Section 3, we present some of our experimental results. Finally, we present our conclusions in Section 4.

1.1 Vector Based Approach

In color images, a color vector of various components describes each pixel. Therefore, it is difficult to integrate the information from those components into one meaningful result. In most 2 cases, a color distance (also known as gradient magnitude) is measured by the Euclidean distance of two vectors. The two schools of vector-based approaches are the gradient magnitude-based approach and the gradient vector-based approach [6].

The gradient magnitude-based approach employs the non-directional differences of vectors to determine the edges in color images. Trahanias and Venetsanopoulos [7] introduced minimum vector dispersion (MVD), which is an vector order statistic operator, to sort a set of n vectors. The result is not only used to define edges but also to reject noise using outlier schema. However, this approach is unable to detect edge directions.

With the gradient vector-based approach, gradient magnitude and gradient direction are both

employed to determine the edges in color images. Wesolkowski and Jernigan [9] combined the chromatic and intensity differences to create a distance metric. This approach is sensitive to noise since the frequency of noisy pixels is high near the locations of edges. Shafarenko et al. [10] estimated the gradient magnitude of a pixel by the maximum Euclidean distance between that pixel and its 8-connected neighbors and they estimated the gradient direction by the direction of the maximum gradient. Evans and Liu [11] introduced a robust color morphological gradient (RCMG) method, which is an extension of a morphological gradient approach [8]. This method is based on the vector differences in a window and uses an outlier rejection schema. Gradient direction is defined as the normal line, in order to obtain the edge and its error is bounded by 45. The method is able to give a better estimation of gradient magnitudes for existing cases of noisy images. Ruzon and Tomasi [12] proposed the compass edge detection, which employs pre-filtering to reduce noise before the edge detection process. A circular window is split into halves and the color signature difference of each half is computed using the earth mover's distance. The same process is repeated for multiple orientations to produce the maximum difference and associated direction.

The main advantage of the gradient vector-based approach is its ability to produce thinner edges because it often applies a non-maximum suppression stage of the Canny edge detector. Non-maximum suppression employs both gradient magnitude and gradient direction to delete non-maximum local gradients.

1.2 The Mahalanobis Distance

The Euclidean distance, which is an ordinary distance between any two points, is a popular method for measuring color distances in a vector-based approach [7-12]. However, since the Euclidean distance considers the components of hue, saturation, and lightness at the same scale, it may not be an appropriate measurement for color distances. The Mahalanobis distance, which is a statistical distance that was introduced by P. C. Mahalanobis in 1936 [13], is a distance measurement that is based on correlations between variables of different patterns. The Mahalanobis distance can be defined as:

$$d(x, y) = \sqrt{(x - y)^t \mathbf{s}^{-1} (x - y)} \quad (1)$$

where $d(x, y)$ is the Mahalanobis distance between two points $x = (x_1, \dots, x_p)^t$ and $y = (y_1, \dots, y_p)^t$ in p -dimension space and \mathbf{s} is a covariance matrix of two groups of data.

2. OUR PROPOSED METHOD

Our approach is based on finding a local maximum gradient in color images. First, the image gradient is assigned to the change of color vectors, namely a gradient magnitude or a color distance. The Mahalanobis distance is then used to measure a color distance because it can distinguish the difference between hue, saturation, and lightness information. We also used information from connected-neighbor pixels to reduce errors that are due to noisy pixels. Next, we employed the non-maximum suppression stage of the Canny edge detector to find sharp edges. We then applied a threshold to produce the final edge result.

2.1 A Color Distance

A pixel value in an RGB image is assigned to three-color components. A pixel is represented by a discrete integer function $f(x, y) = (R(x, y), G(x, y), B(x, y))$ where (x, y) refers to the spatial dimension in a two-dimensional image plane. $R(x, y)$, $G(x, y)$ and $B(x, y)$ are the red, green, and blue color values in the RGB color space at pixel (x, y) , respectively. The function f maps those three color values to a three-dimensional vector.

Because a mixture of three primary colors presents a pixel in the RGB color space, the distance between any two color vectors does not directly correspond to the difference viewed by human perception [14]. On the contrary, the human perception of colors is more closely related to how the HSV color model views colors [6]. The HSV model separates the hue component that represents the dominant color from the saturation and lightness (value) components. Therefore, the HSV color space is more suitable for any image operators that try to imitate human vision perception. One special function of human vision is to accentuate the contours (edges) of objects and separate them from the background. Edge detection in color images emulates this function of human vision. Therefore, it should be performed in the HSV color space.

For the reasons stated above, our method first converts the input image from the RGB color space into an HSV color space. Now, a pixel is represented by a discrete integer function $g(x, y) = (H(x, y), S(x, y), V(x, y))$ where (x, y) refers to the spatial dimension in a two-dimensional image plane. $H(x, y)$, $S(x, y)$ and $V(x, y)$ are the hue, saturation, and lightness components in the HSV color space at pixel (x, y) , respectively. The function g maps color values to a three-dimensional vector in the HSV color space. Next, the color distance is measured by the Mahalanobis distance and then used later to determine the image gradient. The color distance between pixel (x, y) and pixel (p, q) is represented by $d(\vec{v}, \vec{u})$, which can be achieved by:

$$d(\vec{v}, \vec{u}) = \sqrt{(\vec{v} - \vec{u})^t S^{-1} (\vec{v} - \vec{u})} \quad (2)$$

where vectors \vec{v} and \vec{u} express the HSV color vectors of pixels (x, y) and (p, q) , respectively. $S = [S_h \ 0 \ 0; 0 \ S_s \ 0; 0 \ 0 \ S_v]$ is a covariance matrix. S_h , S_s , and S_v are the variances in hue, saturate, and lightness values, respectively.

2.2 Determine an Image Gradient

We calculated the horizontal and vertical gradient magnitudes of a pixel by computing the color distances between the pixel and its neighbors. The gradient magnitude of the pixel is the maximum of the two gradient magnitudes and the gradient direction is the direction of the maximum gradient. To reduce the errors caused by high frequencies of noisy pixels, we have introduced a new technique for estimating gradient magnitudes. This technique takes into consideration the gradient magnitudes of neighbor pixels when computing the gradient magnitude of a particular pixel. The horizontal gradient magnitude of a pixel is given by:

$$G_x(x, y) = \begin{cases} c & ; c > 0 \\ 0 & ; c \leq 0 \end{cases}$$

and

$$c = d(\vec{v}, \vec{u}) - \max(d(\vec{v}, \vec{r}), d(\vec{u}, \vec{q})) \tag{3}$$

where $G_x(x, y)$ is the horizontal gradient magnitude of pixel (x, y) . Vectors \vec{v} , \vec{u} , \vec{r} , and \vec{q} are the color vectors of pixels (x, y) , $(x+1, y)$, $(x-1, y)$, and $(x+2, y)$. $d(\vec{v}, \vec{u})$ is the color distance between two color vectors \vec{v} and \vec{u} . The vertical gradient magnitude of a pixel is given by:

$$G_y(x, y) = \begin{cases} c & ; c > 0 \\ 0 & ; c \leq 0 \end{cases}$$

and

$$c = d(\vec{v}, \vec{u}) - \max(d(\vec{v}, \vec{r}), d(\vec{u}, \vec{q})) \tag{4}$$

where $G_y(x, y)$ is the vertical gradient magnitude of pixel (x, y) . Vectors \vec{v} , \vec{u} , \vec{r} , and \vec{q} are the color vectors of pixels (x, y) , $(x+1, y)$, $(x-1, y)$, and $(x+2, y)$. $d(\vec{v}, \vec{u})$ is the color distance between two color vectors \vec{v} and \vec{u} .

The final gradient magnitude of a pixel (x, y) is given by:

$$G(x, y) = \max(G_x(x, y), G_y(x, y)) \tag{5}$$

Fig. 1(a) shows a sample of a one-dimensional image with three corrupted noisy pixels at location 50, 80, and 170. The resulting gradient magnitude produced by our new technique (as seen in Fig. 1(b)) indicates that this approach can reduce spurious gradients, which are caused by noisy pixels.

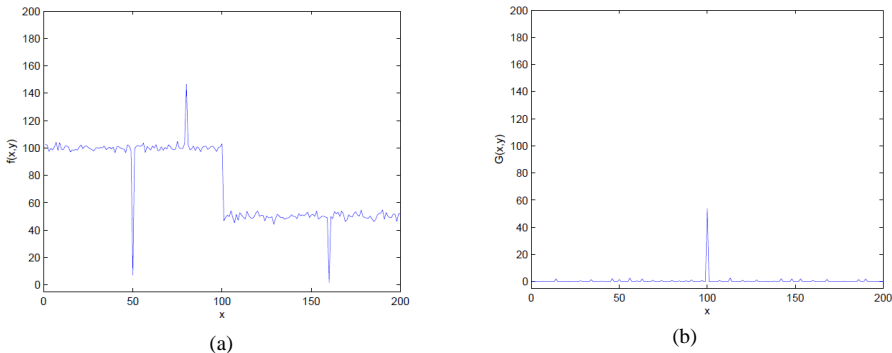


Fig. 1. Determining an image gradient. (a) One-dimensional image, (b) the resulting gradient magnitude.

2.3 Non-Maximum Suppression

Non-maximum suppression, which is proposed in the Canny edge detector [15], preserves all of the local maximal gradients while eliminating other gradients. The main concept of non-maximum suppression is the comparison of the gradient magnitudes of a pixel and its two connected pixels on both negative and positive gradient directions. The pixel is preserved if it has the largest gradient magnitude; otherwise it is suppressed.

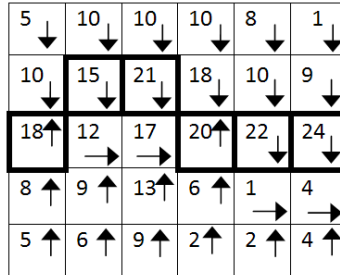


Fig. 2. The resulting edge pixels obtained from non-maximum suppression are indicated by thick borders.

An example of resulting edge found by a non-maximum suppression process is shown in Fig. 2. The gradient magnitudes and directions of these image pixels are shown as numbers and arrows, respectively. Thick borders mark the resulting edge pixels that occur after a non-maximum suppression process. The other pixels are suppressed. Therefore, they are not considered to be edge pixels.

2.4 Detecting Edge Locations

All edge pixels with gradient magnitudes that exceed some threshold (th) are declared to be parts of some edges. The resulting edge pixels can be achieved by

$$E(x,y) = \begin{cases} 1 & ; G(x,y) \geq th \\ 0 & ; G(x,y) < th \end{cases} \quad (6)$$

where $E(x, y)$ is an edge value at pixel (x, y) . $G(x, y)$ is the gradient magnitude at pixel (x, y) and th is a threshold value. The edge value of 1 indicates that (x, y) is an edge pixel and 0 indicates that (x, y) is a non-edge pixel.

3. EXPERIMENTS

To evaluate the performance of our proposed method, we compared its experimental results to those of the state-of-the-art Canny method [5] using both synthesized and real-world images. Moreover, we compared our approach with vector-based classical methods, such as the MVD edge detector [7], the compass operator [12], and the RCMG [11]. For the experiments on synthesized images, we use Pratt’s Figure of Merit (FOM) [16] to access the ground truth which

we obtained by marking all of the pixels with different colors. The Pratt's FOM is defined by

$$Pratt's\ FOM = \frac{1}{\max(I_D, I_I)} \sum_{k=1}^{I_D} \frac{1}{1 + \alpha(d_k)^2} \tag{7}$$

where I_D and I_I are the number of detected edge points and ideal edge points, respectively. d_k is the separation distance of the k_{th} detected edge point that perpendiculars to the line of ideal edge points. The scaling constant α (basically > 0) provides a relative penalty between the smeared and isolated offset edges and is set to 0.2. Pratt's FOM = 1, which corresponds to a perfect match between the detected edge points and the ideal edge points. The parameters for each approach are adjusted until the maximum Pratt's FOM value is obtained. The results of the experiments on the synthesized images are shown in Sections 3.1 and 3.2 and the results on real-world images are shown in Section 3.3.

3.1 Robustness against Errors in Determining Color Distance

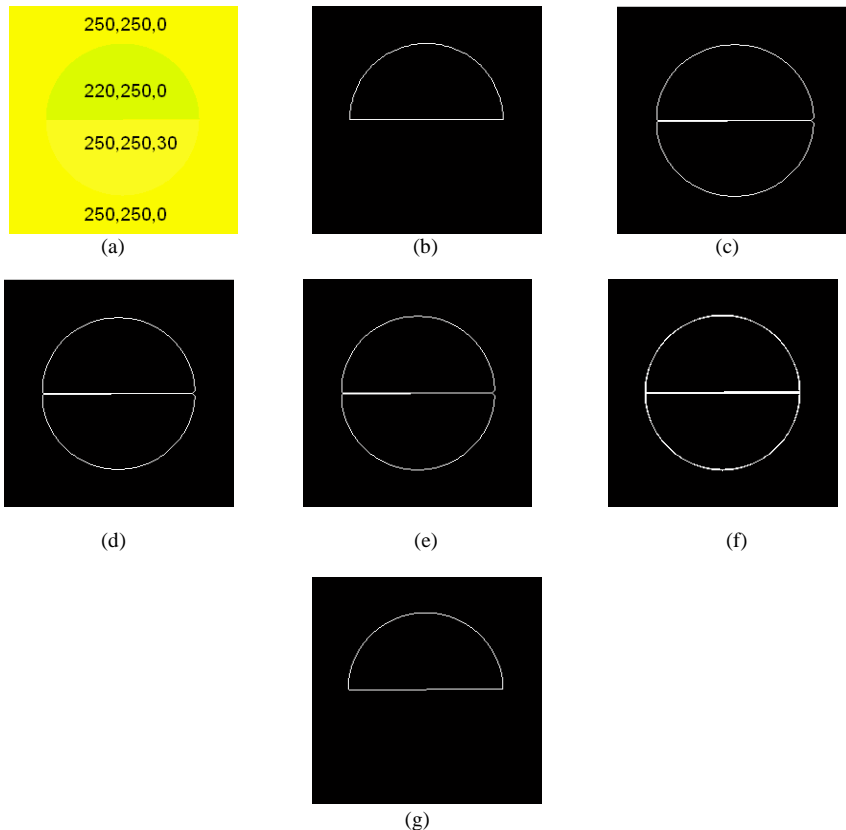


Fig. 3. The experimental results on robustness against errors in color distance determination. (a) Synthesized image, (b) ground truth image, (c) color Canny detector, (d) compass operator, (e) minimum vector dispersion (MVD) method, (f) robust color morphological gradient (RCMG) method, and (g) our approach.

In this section, we investigate the robustness of our approach against errors in estimating color distance. We synthesized a 240×240 pixel image of two semicircles that appear in green (220, 250, 0) and yellow (250, 250, 30) with a yellow background (250, 250, 0), as shown in Fig. 3(a).

The upper semicircle has a different hue from the background, while the lower one has the same hue but different lightness. The ground truth of the image with edges around the upper semicircle is shown in Fig. 3(b). The edge detection results of the color Canny detector, the compass, the MVD, the RCMG, and our approach are shown in Fig. 3(c)–(g), respectively

Moreover, our experiments show that the Pratt’s FOM values of the color Canny detector, the compass, the MVD, the RCMG, and our approach are 0.5659, 0.4916, 0.8042, 0.6514, and 0.9948, respectively. These results show that our approach outperforms other methods because it is able to extract the difference in the case of there being the same hue but a different lightness. The color distances used in other methods are based on the Euclidean distance, which gives the same value for both semicircles. Therefore, the edges of both semicircles are obtained when using a low threshold value, which is inconsistent with the ground truth. Only the use of a high threshold value can detect the ideal edge.

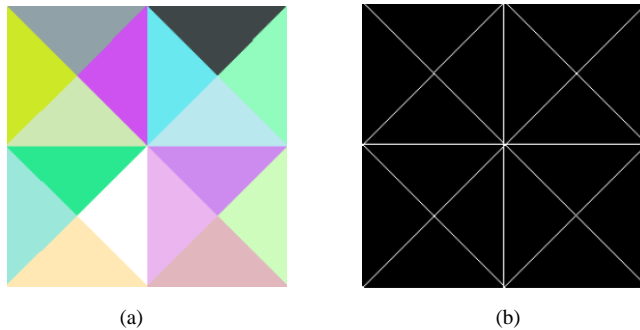


Fig. 4. The experimental results on robustness against noises. (a) Synthesized image, (b) ground truth image.

3.2 Robustness against Noises

We compared our method’s robustness against noise to the following methods: the color Canny detector, compass operator, the MVD, and the RCMG approaches. The range of the parameter for the color Canny detector is $0.1 \leq \alpha \leq 1$. For the compass operator, α is 0.7 to 1.0 for the radius of (3α) of a circular. The range parameters of the MVD are $6 \leq k \leq 10$ and $8 \leq l \leq 14$. For the RCMG detector, the mask size is 5×5 to 7×7 and the parameter s is 4 to 8. For our method, hue, saturate and lightness components are considered to be independent variables. All covariates are set to 0.1 to 0.4 and the parameter th ranged from 0.3 to 1. We used a synthesized image corrupted by white Gaussian noise, salt and pepper noises, an impulsive noise, and a speckle noise for ten different realizations of the noise, 1–30 dB. The noise-free synthesized image and the ground truth image are shown in Fig. 4(a) and (b), respectively.

The Pratt’s FOM values for the simulated test images corrupted by various levels of white Gaussian noise, salt and pepper noises, the impulsive noise, and the speckle noise are shown in Fig. 5(a)–(d), respectively. For the Gaussian-independent noise, the FOM performance of our method and the color Canny method was quite similar and they outperformed other methods.

One exception is that the compass operator gave better results for SNRs below 12 dB. For salt

and pepper noises, the color Canny operator and the RCMG method gave similar results, while the compass and MVD methods performed quite the same. However, our approach outperformed all of the methods. For the impulsive noise, the FOM performance for the color Canny operator and the compass method were broadly similar. The RCMG and the MVD methods showed similar patterns in terms of how they handled the impulsive noise. Again, our approach provided better results than other methods here. For the speckle noise, all of the methods, except the compass method, gave better results than our approach for SNRs below 5 dB. However, our approach outperformed every method for SNRs above 5 dB. For all noise, the Pratt's FOM values from the color Canny detector, the compass, the MVD, and the RCMG methods were generally lower than our approach.

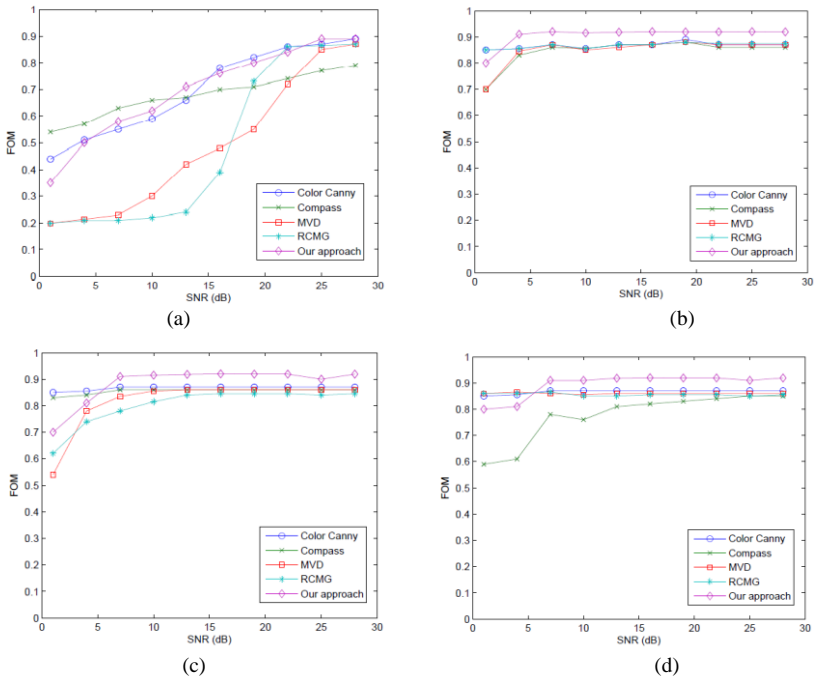


Fig. 5. Pratt's Figure of Merit (FOM) results from the color Canny detector, the compass, the minimum vector dispersion (MVD), the robust color morphological gradient (RCMG), and our methods on (a) Gaussian-Independent noise, (b) salt and pepper noises, (c) impulsive noise, and (d) speckle noise. SNR=signal-to-noise ratio.

3.3 Experimental Results on Real-World Images

For real-world images, we obtained experimental results from the color Canny detector, the compass, the MVD, the RCMG, and our methods, as presented in Figs. 6 and 7. Fig. 6(a) shows a pepper image. Fig. 6(b)–(f) shows the edge points that resulted from the color Canny detector, the compass, the MVD, the RCMG, and our methods, respectively. The color Canny detector and the MVD methods produced thicker edges than other approaches because the color Canny detector obtains its results from the operation OR from the three color channels and the MVD

method does not apply non-maximal suppression. The results produced by the compass operator (shown in Fig. 6(c)) displayed many spurious edges since edge points usually shift a few points from the ground truth pixels. This method responds strongly to color fluctuations. The results from the RCMG method (presented in Fig. 6(e)) showed broken edges. This method may possibly compute a wrong gradient direction since it defines the perpendicular to the obtained edge line as being the gradient direction. Our method produced thinner and more continuous edges than other methods, as shown in Fig. 6(f). In another experiment, the building image (shown in Fig. 7(a)) was served as input. The top of the building, as indicated by a circle, is varied in lightness. Our approach showed edge lines in this area, while the compass operator could not detect the edge pixels. Although the color Canny detector, the MVD, and the RCMG methods were able to produce edge lines in the circle, the edge lines were thick, spurious, or broken, which are possibly due the reasons mentioned above.

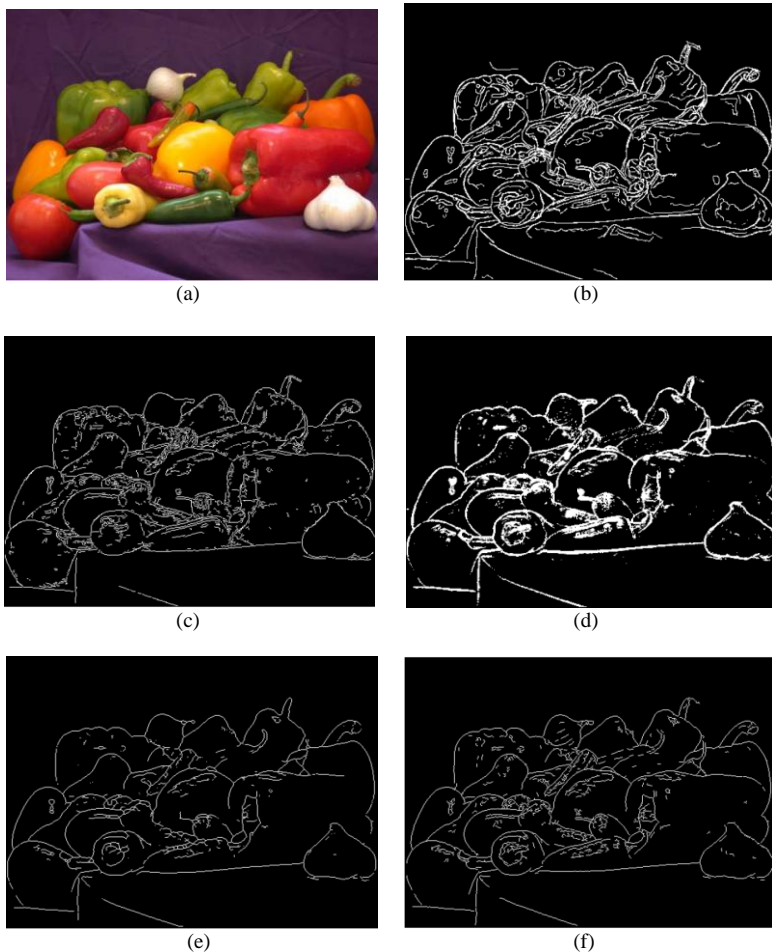


Fig. 6. Results of edge detection operators on a real-world. (a) A pepper image, (b) color Canny detector, (c) compass operator, (d) the minimum vector dispersion (MVD) method, (e) the robust color morphological gradient (RCMG) method, and (f) our approach.

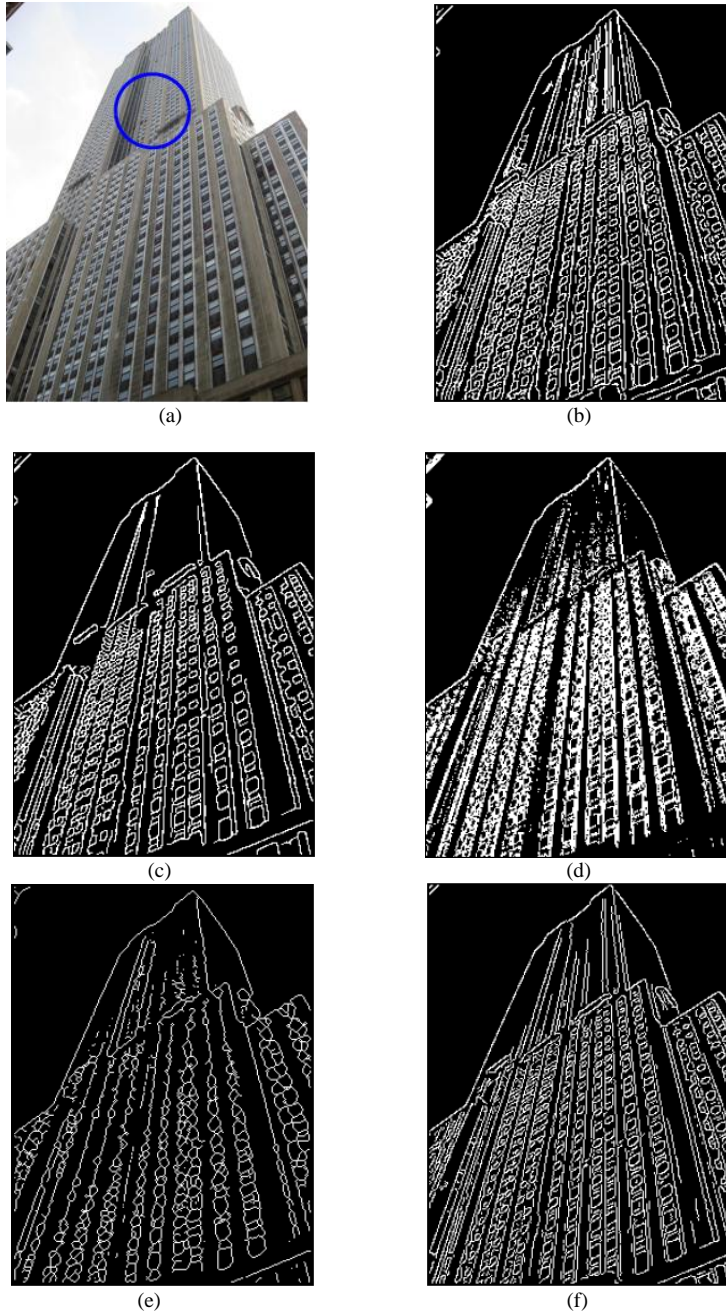


Fig. 7. Results of edge detection operators on a real-world. (a) A building image, (b) color Canny detector, (c) compass operator, (d) the minimum vector dispersion (MVD) method, (e) the robust color morphological gradient (RCMG) method, and (f) our approach.

4. CONCLUSION

We have proposed a novel color edge detection that takes advantage of the HSV color space and applies the Mahalanobis distance to better estimate the color distance of two vectors. The main idea is to consider the hue, saturation, and lightness components of a pixel separately when computing the color distance of two pixels. Our approach outperformed other methods that measure color distances using the Euclidean distance. This is due to the fact that it can detect the edges that are marked by the change in lightness but not hue. In addition, we also proposed a new technique to determine pixel gradients by using the information from connected neighbor pixels to reduce the errors caused by high frequencies of noisy pixels. This approach has advantages over blurring techniques since it does not eliminate image details. To test our proposed method, we performed many experiments on both simulated test images and real-world images. The results have demonstrated that our method can outperform many of the existing vector-based edge detection methods, even when numerous kinds of noises are presented.

REFERENCES

- [1] C.L. Novak and S.A. Shafer, "Color edge detection," in *Proceedings of DARPA Image Understanding Workshop*, Los Angeles, CA, 1987, pp.35-37.
- [2] A. Koschan and M. Abidi, "Detection and classification of edges in color images," *IEEE Signal Processing Magazine*, vol. 22, no. 1, pp. 64-73, 2005.
- [3] M. Hedley and H. Yan, "Segmentation of color images using spatial and color space information," *Journal of Electronic Imaging*, vol. 1, no. 4, pp. 374-380, 1992.
- [4] S. Di Zenzo, "A note on the gradient of a multi-image," *Computer Vision, Graphics, and Image Processing*, vol. 33, no. 1, pp. 116-125, 1986.
- [5] J. Fan, D. K. Yau, A. K. Elmagarmid, and W. G. Aref, "Automatic image segmentation by integrating color-edge extraction and seeded region growing," *IEEE Transactions on Image Processing*, vol. 10, no. 10, pp. 1454-1466, 2001.
- [6] E. Nezhadarya and R. K. Ward, "A new scheme for robust gradient vector estimation in color images," *IEEE Transactions on Image Processing*, vol. 20, no. 8, pp. 2211-2220, 2011.
- [7] P. E. Trahanias and A. N. Venetsanopoulos, "Color edge detection using vector order statistics," *IEEE Transactions on Image Processing*, vol. 2, no. 2, pp. 259-264, 1993.
- [8] J. Lee, R. M. Haralick, and L. G. Shapiro, "Morphologic edge detection," *IEEE Journal of Robotics and Automation*, vol. 3, no. 2, pp. 142-156, 1987.
- [9] S. Wesolkowski and E. Jernigan, "Color edge detection in RGB using jointly Euclidean distance and vector angle," in *Proceedings of the IAPR Vision Interface Conference*, Trois-Rivieres, Canada, 1999, pp. 9-16.
- [10] L. Shafarenko, M. Petrou, and J. Kittler, "Automatic watershed segmentation of randomly textured color images," *IEEE Transactions on Image Processing*, vol. 6, no. 11, pp. 1530-1544, 1997.
- [11] A. N. Evans and X. U. Liu, "A morphological gradient approach to color edge detection," *IEEE Transactions on Image Processing*, vol. 15, no. 6, pp. 1454-1463, 2006.
- [12] M. A. Ruzon and C. Tomasi, "Color edge detection with the compass operator," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Ft. Collins, CO, 1999, pp. 160-166.
- [13] P. C. Mahalanobis, "On the generalized distance in statistics," *Proceedings of the National Institute of Sciences (Calcutta)*, vol. II, no. 1, pp. 49-55, 1936.
- [14] P. Chauhan and R. V. Shahabade, "Edge detection comparison on various color spaces using histogram equalization," *International Journal of Advance Computational Engineering and Networking*, vol. 1, no. 4, pp. 7-10, 2013.

- [15] J. Canny, "A computational approach to edge detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 8, no. 6, pp. 679-698, 1986.
- [16] I. E. Abdou and W. Pratt, "Quantitative design and evaluation of enhancement/thresholding edge detectors," *Proceedings of the IEEE*, vol. 67, no. 5, pp. 753-763, 1979.



Kittiya Khongkrapan

She received the B.Sc. degree in Mathematics and M.Sc. degree in Computer Science from Prince of Songkla University (PSU), Thailand, in 1991 and 2000, respectively. She received Ph.D. degree in Electrical and Computer Engineering from King Mongkut's University of Technology Thonburi (KMUTT), Thailand, in 2010. She is currently a lecturer at the faculty of Science and Technology, PSU. Her research interests include computer vision and image processing.