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An Efficient Color Edge Detection using a Mahalanobis Distance

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Abstract— The performance of edge detection often relies on its ability to correctly determine the dissimilarities of connected pixels. For gray-scale images, the dissimilarity of two pixels is estimated by a scalar difference of their intensities and for color images, by a vector difference (color distance) of the three color components. A color distance is typically measured by the Euclidean distance in the RGB color space. 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 taking advantage of the HSV color space and the Mahalanobis distance. The HSV space models colors in manner similar to human perception. The Mahalanobis distance independently considers the hue, saturation, and lightness and gives them different degrees of contribution to the measurement of color distances. Therefore, our method is robust against the change in lightness comparing to previous approaches. Furthermore, we introduce a noise-resistant technique to determine image gradients. Various experiments on simulated and real-world images show that our approach outperforms several existing methods, especially when images are varied in lightness or corrupted by noise..

Keywords— Edge detection, Color image, Mahalanobis distance

1. INTRODUCTION

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

Typically, edge detection is performed on gray-scale images when edges are defined as discontinuities or 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 into gray-scale. However, this approach may fail to detect any edge in color images characterized by the change in pixel hue but not pixel intensity. In fact, Novak and Shafer [1] reports that gray-scale edge detection techniques can only account for 90% of the edge points in color images, while the remaining 10% require some color edge detection techniques.

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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. There are two major approaches for color edge detection techniques, monochromatic-based and vector-based approaches [2].

Monochromatic-based approach is extended from the gray-scale 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 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.

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 gray-scale edge detection techniques [2] as in the monochromatic-based approach.

The main contribution of our paper is to introduce efficient vector-based edge detection for RGB color images. Our proposed method considers the nature of colors such that 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, saturate and lightness separately. This method is robust against the change of lightness than previous methods that employ the Euclidean distance in measuring color distances [6-12]. Additionally, we propose a new technique to reduce the error 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 gradient magnitude and gradient direction without eliminating image details.

This paper is organized as follow. Following this initial introduction, Section 1 of this paper 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 experimental results. Finally, conclusions are drawn in Section 4.

1.1 Vector Based Approach

In color images, each pixel is described by a color vector of various components; 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 gradient magnitude-based approach and gradient vector-based approach [6].

The gradient magnitude-based approach employs non-directional differences of vectors to determine edges in color images. Trahanias and Venestsanopoulos [7] introduce Minimum vector dispersion (MVD), an 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.

In gradient vector-base approach, both gradient magnitude and gradient direction are employed to determine edges in color images. Wesolkowski and Jernigan [9] combine the differences of chromatic and intensity 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] estimate the gradient magnitude of a pixel by the maximum Euclidean distance between that pixel and its 8-connected neighbors and the gradient direction by the direction of the maximum gradient. Evans and Liu [11] introduce 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 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 propose the compass edge detection [12] which employs prefiltering to reduce noise before edge detection process. A circular window is split into halves and the difference color signature of each half is computed using the earth moving 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 (NMS) of the Canny edge detector. NMS employs both gradient magnitude and gradient direction to delete non-maximum local gradients.

1.2 A Mahalanobis Distance

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

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

where $d(x, y)$ is the Mahalanobis distance between two points $x = (x_1, \ldots, x_p)^t$ and $y = (y_1, \ldots, y_p)^t$ in p-dimension space and 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 used to measure a color distance because it can distinguish the difference between hue, saturation, and lightness information. We also use information from connected-neighbor pixels to reduce error due to noisy pixels. Next, we employ the non-maximum suppression stage of the Canny edge detector to find sharp edges. We then apply 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 2-dimensional image plane. $R(x, y)$, $G(x, y)$ and $B(x, y)$ are 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-dimension vector.

Because a pixel in the RGB color space is presented by a mixture of three primary colors, the distance between any two color vectors does not directly correspond to the difference viewed by human perception [16]. On the contrary, human perception of colors is more closely related to how the HSV color model views colors [17]. The HSV model separates hue component that represents the dominant color from 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 above reason, our method first converts the input image from the RGB color space into 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 2-dimensional image plane. $H(x, y)$, $S(x, y)$ and $V(x, y)$ are hue, saturate, and lightness components in the HSV color space at pixel (x, y), respectively. The function g maps color values to a three-dimension (3-D) vector in the HSV color space. Next, the color distance is measured by the Mahalanobis distance and then used later to determined the image gradient. The color distance between pixel (x, y) and pixel (p, q) is represented by $d(\vec{v},\vec{u})$ that can be achieved by

$$d(\vec{v},\vec{u}) = \sqrt{(\vec{v}-\vec{u})^{t}\mathbf{s}^{-1}(\vec{v}-\vec{u})} \qquad (2)$$

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 variances on hue, saturate, and lightness values, respectively.

2.2 Determine an image gradient

We calculate the horizontal and vertical gradient magnitudes of a pixel by computing color distances between this 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 error caused by high frequencies of noisy pixels, we introduce a new technique for estimating gradient magnitudes. This technique takes in consideration the gradient magnitudes of neighbor pixels when computing 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

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

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

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

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

$$G(x,y)=\max(G_x(x,y),G_y(x,y)) \qquad (5)$$

Figure 1(a) shows a sample of 1-dimensional image with 3 corrupted noisy pixels at location 50, 80, and 170. The resulting gradient magnitude produced by our new technique (as seen in Figure 1(b)) indicates that this approach can reduce spurious gradient caused by noisy pixels.

(a) 1-dimensional image (b) The resulting gradient magnitude

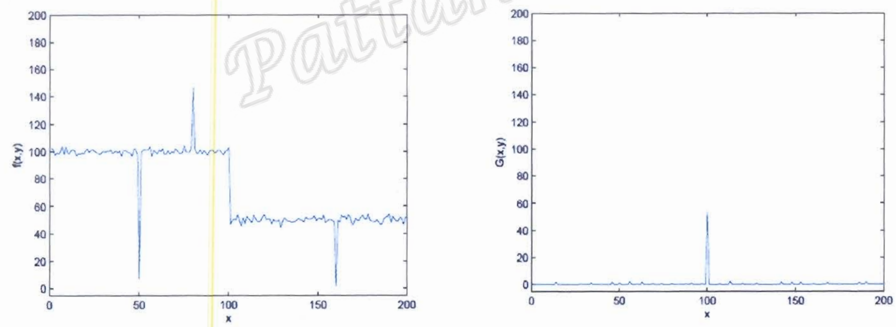

Fig. 1. Determining an image gradient

2.3 Non-maximum suppression

Non-maximum suppression, proposed in Canny edge detector [14], preserves all local maximal gradients while eliminating other gradients. The main concept of non-maximum suppression is the comparison of 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.

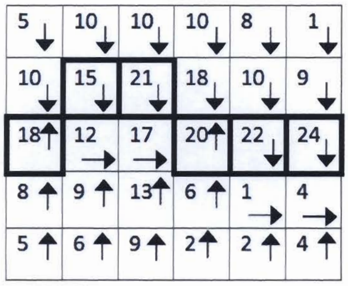

Fig. 2. The resulting edge pixels obtained from NMS indicated by thick border lines

An example of resulting edge found by a non-maximum suppression process is shown in Figure 2. The gradient magnitudes and directions of these image pixels are shown as numbers and arrows, respectively. The resulting edge pixels after a non-maximum suppression process are marked by thick border lines. The other pixels are suppressed; therefore; they are not considered edge pixels.

2.4 Detecting edge locations

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

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

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 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 compare its experimental results to those of the state-of-the-art Canny method [5] using both synthesized and real-world images. Moreover, we compare our approach with vector-based classical methods such as the Minimum Vector Dispersion (MVD) edge detector [7], the compass operator [12], and the Robust Color Morphological Gradient (RCMG) [11]. For the experiments on synthesized images, we use Pratt's Figure of Merit (Pratt's FOM) [15] to access the ground truth, which obtained by marking all pixels with different colors than its neighbors. 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 normal 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. A Pratt's FOM = 1 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 Section 3.1 and 3.2 and the results on real-world images are shown in Section 3.3.

3.1 Robustness against error in color distance determination

In this section, we investigate the robustness of our approach against error in color distance estimation. We synthesize a 240x240-pixel image of two semicircles that appear in green (220, 250, 0) and yellow (250, 250, 30) with yellow background (250, 250, 0) as shown in Figure 3(a).

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

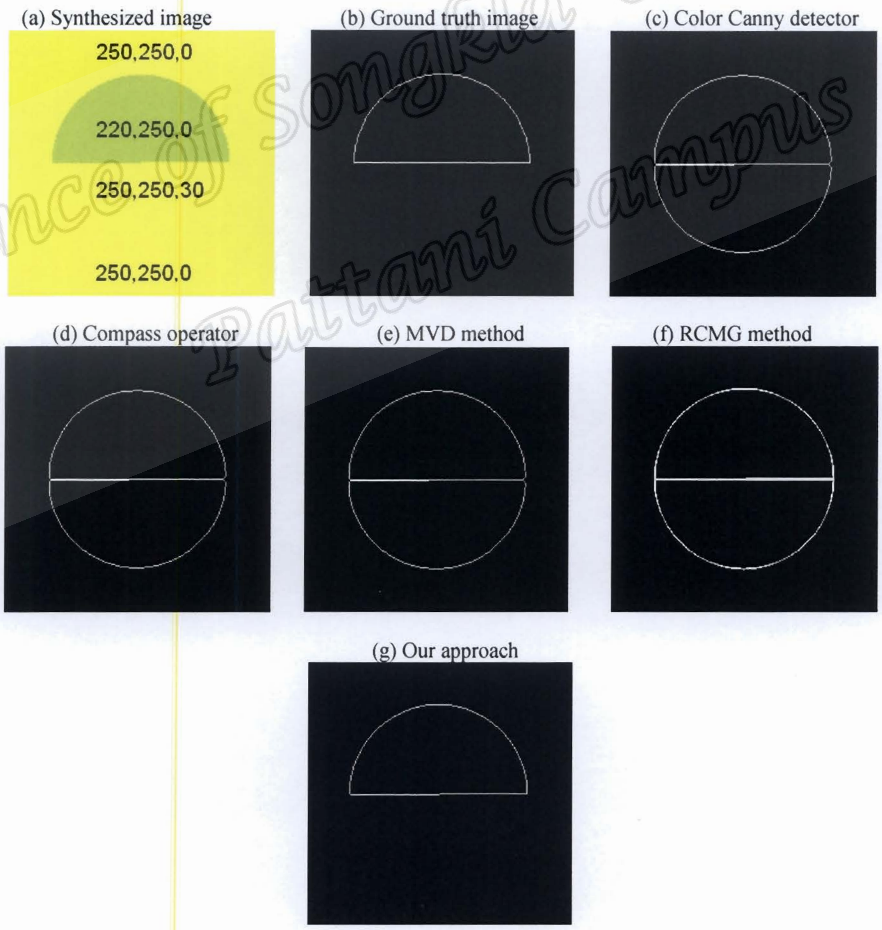

Fig. 3. The experimental results on robustness against error in color distance determination

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. This result shows that our approach outperforms other methods because it is able to extract the difference in the case of same hue but 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.

3.2 Robustness against noises

We compare the robustness against noise of our method to those following methods: the color Canny detector, compass operator, MVD, and RCMG approaches. The range of 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 5x5 to 7x7 and the parameter s is 4 to 8. For our method, hue, saturate and lightness components are considered independent variables. All covariant are set to 0.1 to 0.4 and the parameter th ranges 0.3 to 1. We use 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 Figure 4(a) and (b), respectively.

(a) Synthesized image

Fig. 4. The experimental result on robustness against noises

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 Figure 5 (a)-(d), respectively. For the Gaussian-independent noise, the FOM performance of our method and the color Canny method is quite similar and they outperform other methods.

One exception is that the compass operator gives better result for SNRs below 12 dB. For salt and pepper noises, the color Canny operator and the RCMG method give similar results while the compass and MVD methods perform quite the same. However, our approach outperforms all methods. For the impulsive noise, the FOM performance for the color Canny operator and the compass method are broadly similar. The RCMG and the MVD methods show similar patterns on how they handle the impulsive noise. Again, our approach provides better results than other methods here. For the speckle noise, all methods except the compass method give better results than our approach for SNRs below 5 dB; however, our approach outperforms every method for

SNRs above 5 *dB*. For all noise, the Pratt's FOM values from the color Canter detector, the compass, the MVD, and the RCMG methods are generally lower than our approach.

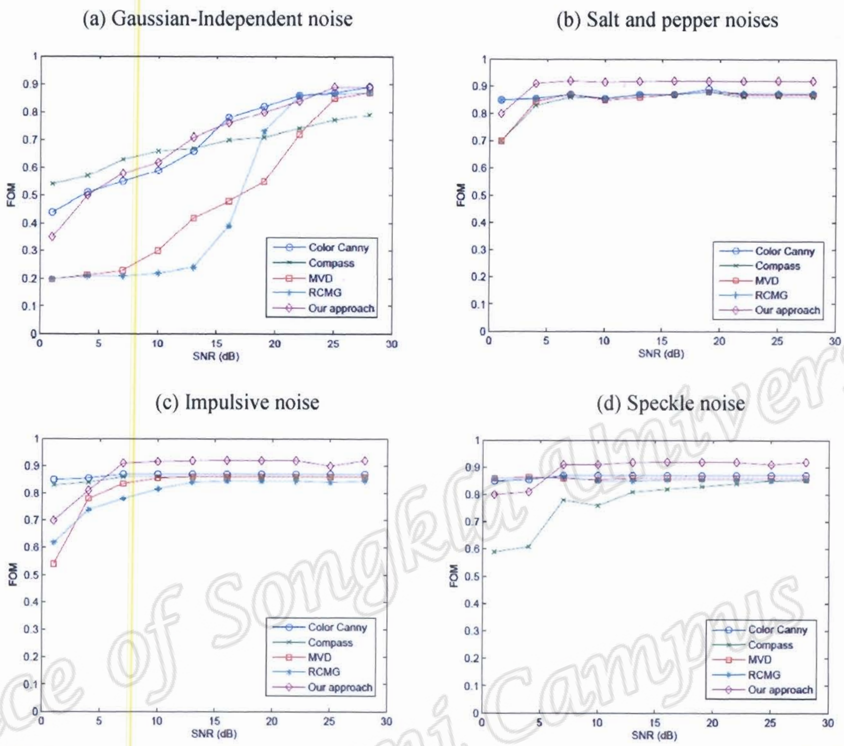

Fig. 5. Pratt's FOM results from the color Canny detector, the compass, the MVD, the RCMG, and our methods on (a) Gaussian-Independent noise (b) Salt and pepper noises (c) Impulsive noise (d) Speckle noise

3.3 Experimental results on real-world images

For real-world images, we obtain experimental results from the color Canny detector, the compass, the MVD, the RCMG, and our methods as presented in Figure 6 and 7. Figure 6 (a) shows a pepper image. Figure 6(b)-(f) show edge points resulting from the color Canny detector, the compass, the MVD, the RCMG, and our methods, respectively. The color Canny detector and the MVD methods produce thicker edges than other approaches because the color Canny detector obtains 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 Figure 6 (c)) display many spurious edges since edge points usually shift a few points from the ground truth pixels. The method responds strongly to color fluctuations. The results from the RCMG method (presented in Figure 6 (e)) shows broken edges. This method may possibly compute a wrong gradient direction since it defines the normal to the obtained edge line as gradient direction. Our method produces thinner and more continuous edge than other methods as shown in Figure 6 (f). In another experiment, the building image (shown in 7(a)) is served as input. The top of the building, as indicated by a circle, is varied in lightness. Our approach shows edge lines in this area, while the compass operator cannot detect edge pixels. Although the color Canny detector, the MVD, and the RCMG methods can produces edge lines in the circle, the edge lines are thick, spurious, or broken, possibly from the reasons mentioned above.

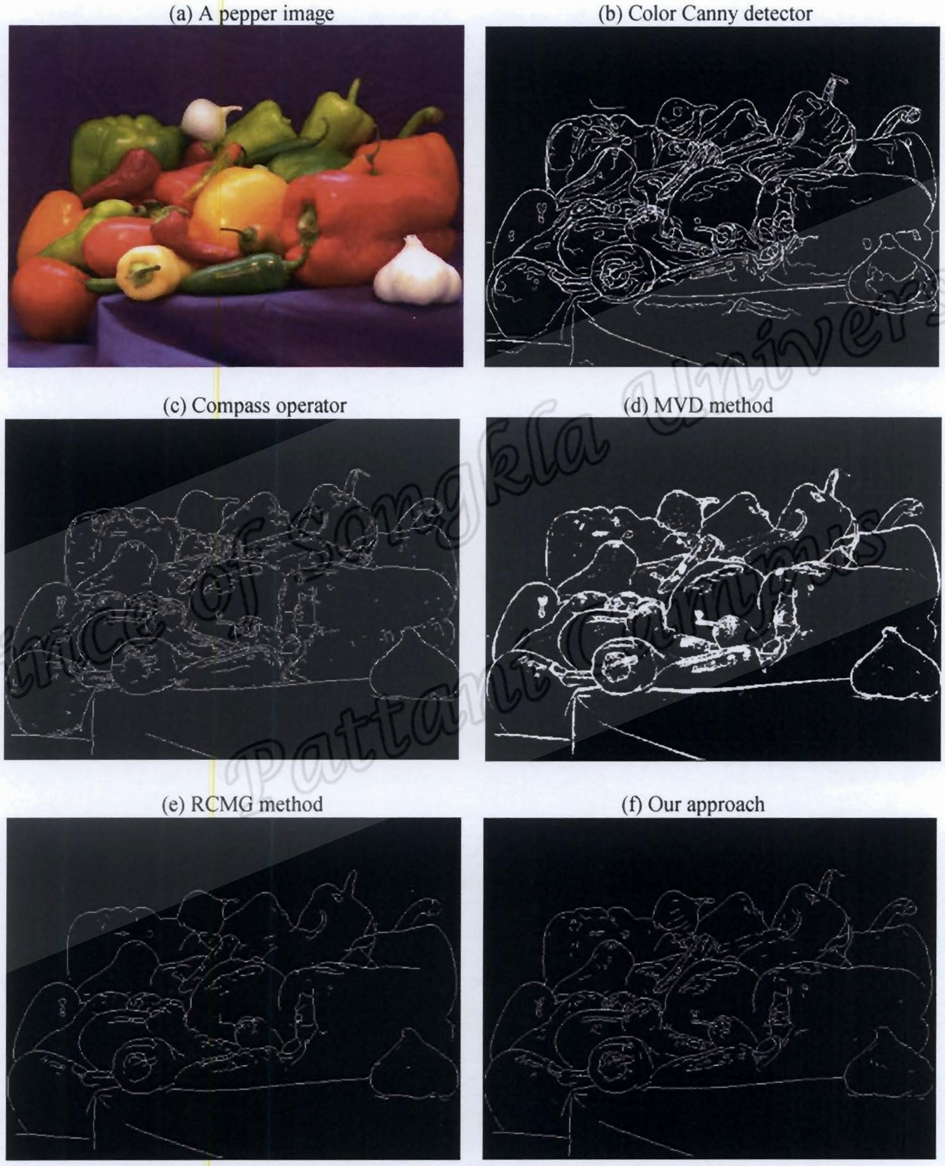

Fig. 6. Results of edge detection operators on a real-world

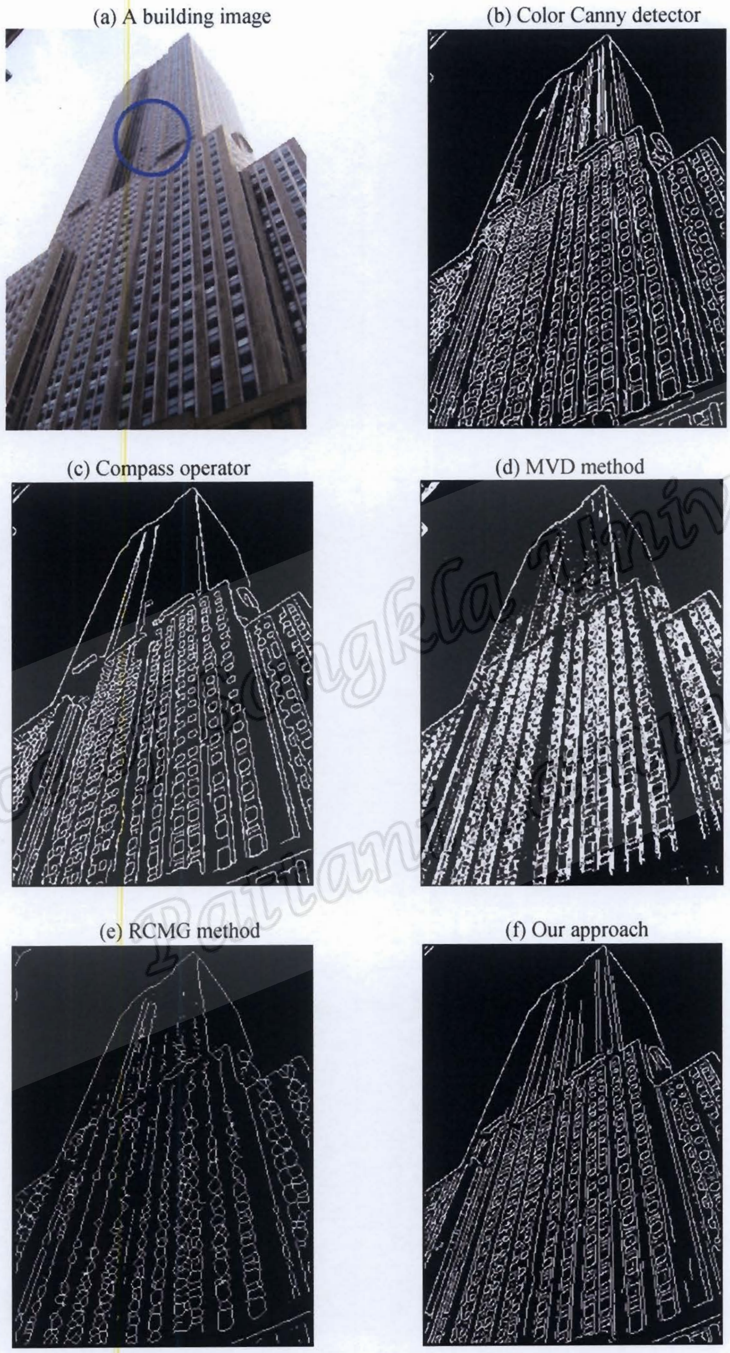

Fig. 7. Results of edge detection operators on a real-world

4. Conclusion

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

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