International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6.14 | Impact Factor (2013): 4.438

Detection of Edges in Color Images to Estimate Plant Diseases

Snehal M. Kalmegh[1], S. V. Dhopte[2]

[1]M. E. Information Technology, P. R. M. I. T. R, Badnera, Amravati.

[2]Associate Professor, Department of Information Technology, P. R. M. I. T. R, Badnera, Amravati

Abstract: ***The study of plant disease refer to the studies of visually observable patterns of a particular plant. Nowadays crops face many traits/diseases. Damage of the insect is one of the major trait/disease. A common practice for plant scientists is to estimate the damage of plant (leaf, stem) because of disease by an eye on a scale based on percentage of affected area. It results in subjectivity and low throughput .We present techniques for the detection and classification of edges in color images of plants. Edge detection is one of the most important tasks in image processing. It denotes the procedure of detecting meaningful discontinuities (edges) of the image function. The accuracy in detecting these discontinuities (edge detection) and the efficiency in implementing these operations are important criteria for using an algorithm and different operators in the area of computer vision. This paper provides a advances in various methods used to study plant diseases using image processing. The methods studied are for increasing throughput.***

Keywords: edge detection, color image, classification of edges.

1. Introduction

India is an agricultural country where in about 70% of the population depends on agriculture. The image processing can be used in agricultural applications for following purposes:
1. To detect diseased leaf, stem, fruit.
2. To quantify affected area by disease.
3. To find shape of affected area.
4. To determine color of affected area.
5. To determine size & shape of fruits.
Etc.

Figure 1: potato leaf affected by late blight

The above potato leaf shows that the plant is suffering from disease or the deficiency. Figure 1 shows the potato leaf affected by late blight.

Figure 2: leaf symptoms of canker on top and bottom leaves

In most of the cases pests or diseases are seen on the leaves or stems of the plant. Therefore identification of plants, leaves, stems and finding out the pest or diseases, percentage of the pest or disease incidence, symptoms of the pest or disease attack, plays a key role in successful cultivation of crops. It is found that diseases cause heavy crop losses amounting to several billion dollars annually. Precise quantification of these visually observed diseases, pests, traits has not studied yet because of the complexity of visual patterns. Hence there has been increasing demand for more specific and sophisticated image pattern understanding. Edge detection is a fundamental tool in image processing and computer vision in the areas of feature detection and feature extraction. The main aim of edge detection is to identifying points in a digital image of plants at which the image brightness changes sharply or more formally.

1.1 Edge Detection

Image edge detection deals with extracting edges in an image by identifying pixels where the Intensity variation is high. It is a fundamental tool used in most image processing applications to obtain information from the frames as a precursor step to feature extraction and object segmentation. This process detects outlines of an object and boundaries between objects and the background in the image. The edge is the set of the pixel, whose surrounding gray is rapidly changing. The internal characteristics of the Edge-dividing area are the same, while different areas have different characteristics. The edge is the basic characteristics of the image. There is a lot of information of the image in the edge. Edge detection is to extract the characteristics of discrete parts by the difference in the image characteristics of the object, and then to determine the image area according to the closed edge.

1.2Edges in Color Images

Edges in gray-level images can be thought of as pixel locations of abrupt gray-level change. A change in the image function can be described by a gradient that points in the direction of the largest growth of the image function. Therefore, one edge detection technique is to measure the gradient vector magnitude at pixel locations. This method works best when the gray-level transition is quite abrupt, like a step function. As the transition region gets wider, it is more advantageous to apply second-order derivatives like the Laplacian. The potential edge pixel locations can then be described by zero-crossings in the results. While edge detection in gray-level images is a well-established area, edge detection in color images has not received the same attention. The fundamental difference between color images and gray-level images is that, in a color image, a color vector(which generally consists of three components) is assigned to a pixel, while a scalar gray-level is assigned to a pixel of a gray-level image. Thus, in color image processing, vector-valued image functions are treated instead of scalar image functions (as in gray-level image processing). The techniques used for this can be subdivided on the basis of their principle procedures into two classes:

- Monochromatic-based techniques treat information from the individual color channels or color vector components first separately and then combine together the individual results gained.
- Vector-valued techniques treat the color information as color vectors in a vector space provided with a vector norm.

Up to now, most of the color edge detection methods are monochromatic-based techniques, which produce, in general, better than when traditional gray-value techniques are applied. In this overview, we focus mainly on vector-valued techniques because it is easy to understand how to apply common edge detection schemes to every image.

2. Approaches of edge detection

There are many methods for edge detection, but most of them can be grouped into two categories, search-based and zero-crossing based. The search-based methods detect edges by first computing a measure of edge strength, usually a first-order derivative expression such as the gradient magnitude, and then searching for local directional maxima of the gradient magnitude using a computed estimate of the local orientation of the edge, usually the gradient direction. The zero-crossing based methods search for zero crossings in a second-order derivative expression computed from the image in order to find edges, usually the zero-crossings of the Laplacian or the zero crossings of a non-linear differential expression. As a pre-processing step to edge detection, a smoothing stage, typically Gaussian smoothing, is almost always applied.

2.1 Edge Detection Based on Gradient Operator

The edge is the place where image gray value is changing rapidly, so the method based on the Derivation of the gradient operator is most widely used. The classical gradient operators are Sobel operator [1], Prewitt operator [2], Roberts’s operator, Laplacian operator.

2.2 Edge Detection Based on the Optimum Operator

The gradient of the image edge is the maximum value, that is, the inflection point of the gray image is the edge. From the mathematical point of view, inflection point of the second derivative of the function is 0. Detecting this point, whose second derivative is 0 is a way of edge detection, for example, Marr-Hildreth operator [3], Canny operator[4,5].

2.3Multi Scale Edge Detection

Wavelet transform is particularly suitable for signal mutation detection and edge detection. Rosenfeld [6] suggested a combined consideration on the edge detected by multiple dimensions operator, by applying multiple scales of the different operators, and put forward some combination rules.

2.4 Edge Detection Based on Ant Colony Optimization

(ACO) is a nature-inspired optimization algorithm [1], [2], motivated by the natural phenomenon that ants deposit pheromone on the ground in order to mark some favorable path.

2.5 Some Other Methods

The adaptive smooth filter method the iterative computation of the smoothing filtering sharpens the signal edge. And then to detect the edge can get a high positioning accuracy. There are also methods based on integral transform and based on tensor. There are many different methods which gives the edge detection mechanism. Out of which one technique is known as vector valued technique which gives in next segment as follows.

3. Vector-valued techniques

In some early publications on color edge detection, vector-valued techniques were suggested that replaced gray-level differences of adjacent pixels in some way by vector differences [17], [24]. Huntsberger and Descalzi [11] used fuzzy membership values, while Pietikainen and Harwood [17] used histograms of vector differences. Yang and Tsai [30] and Tao and Huang [25] used vector projections, but the first projected colors into grayscale, while the latter projected vector differences onto segments connecting color clusters.

However, these simple difference operators do not represent the state of the art in edge detection in either gray level image processing or in color image processing.

Figure 3: Results of edge detection applied to the color image Lena. (a) Original color image. (b) Gray-level representation. (c) Results for a color variant of the Canny operator. (d) Results of the gray-level algorithm of the Canny operator

4. Cumani Operator

For edge detection in color or multispectral images, Cumani suggests the extension of procedures based on the second partial derivatives of the image functions [4]. A three-channel color image C is regarded as a two-dimensional (2-D) vector field

$$C(x, y) = (C1(x, y), C2(x, y), C3(x, y)) \quad (1)$$

With the three components C1(x, y), C2(x, y), and C3(x, y) in the RGB space, these vector components correspond to the components R(x, y), G(x, y), and B(x, y) for the RGB color channels (or the long, middle, and short wave spectral transmission, respectively). The notation Ci(x, y) is given at this point, on the one hand, for a compact representation. On the other hand, it should be made clear that this technique is applicable, in general, for n-channel color images. In this connection, it is always assumed that a Euclidian metric exists for the n-dimensional vector space. Therefore, this technique cannot be easily used for edge detection in the HSI, CIELUV, or CIELAB space. The squared local contrast S(p; n) at p = (x, y) is defined [4] as a quadratic norm of the directional derivatives of the image function C toward the unit vector n = $(n1, n2)$ by

$$S(p;n)=Kn_1^2+2Fn_1n_2+Hn_2^2 \quad (2)$$

The abbreviations are defined as

$$K=\sum_{i=0}^{3}\cdot\frac{\delta Ci}{\delta x}\cdot\frac{\delta Ci}{\delta x}$$
$$F=\sum_{i=0}^{3}\cdot\frac{\delta Ci}{\delta x}\cdot\frac{\delta Ci}{\delta y}$$
$$H=\sum_{i=0}^{3}\cdot\frac{\delta Ci}{\delta y}\cdot\frac{\delta Ci}{\delta y} \quad (3)$$

The eigen values of the matrix

$$A=\begin{pmatrix} K & F \\ F & H \end{pmatrix} \quad (4)$$

Coincide with the extreme values of S (p;n) and are obtained if n is the corresponding eigenvector. The extreme values $\lambda\pm$ and the corresponding eigenvectors are given by

$$\lambda\pm=\frac{K+H}{2}\pm\sqrt{\frac{(K+H)^2}{4}+F^2} \text{ AND}$$

$$n\pm=(\cos(\theta\pm),\sin(\theta\pm)), \quad (5)$$

With $\theta_- = \theta_+ + (\pi/2)$ and

$$\theta_+=\begin{cases} \frac{\pi}{4} IF(K-H)=0, F>0 \\ \frac{-\pi}{4} If(K-H)=0, F<0 \\ \frac{1}{2}\tan^{-1}\left(\frac{2F}{K-H}\right), IFK=F=H=0 \end{cases}$$

Undefined, if $K = F = H = 0$, and

.

In the one-channel case, $\lambda_\pm$ corresponds to the gradient, and $n_\pm$ and $\theta_\pm$ give the direction of the strongest and the weakest magnitude. The two latter terms thus correspond to the gradient direction. Since only the direction of the steepest magnitude is of importance for the extraction of edge points, λ_-, n_-, and θ_- are not further addressed. The squared local contrast of the vector-valued image function C, dependent on location and direction, is defined by S(p; n_+). The maximum squared local contrast λ_+ was clearly defined as a maximum of S(p; n_+) over the possible directions n_+, while the direction of the maximum magnitude is clearly determined only up to the orientation. Edge points, i.e., discontinuities of the image function that are characterized by a particularly high contrast, are sought. The maxima of λ+ are calculated by deriving the function λ_+(p), which is represented as a function of the location. Subsequently, the zeros of the derivative, which represent the maxima, are to be determined. In order to find the zeros of λ_+(p) defined in (5), the derivatives of this function can also be formed in direction n_+.

$$\nabla\lambda_+\cdot n_+=\nabla S(p;n_+)\cdot n_+. \quad (6)$$

Therefore, the derivative of λ+ is defined by
DS(p; n) with
DS(p; n)= $\nabla\lambda_+$

$$n_+ = Kxn_1^3+(Ky+2Fx)n_1^2n2+(Hx+2Fy)n1n_2^2+Hyn_2 \quad (7)$$

Where the indices x and y denote the corresponding derivatives to x and y, respectively, and the index + in the components of n_+ are omitted for simplification. In the one-channel case, $\lambda_\pm$ corresponds to the absolute value of the gradient.DS(p; n_+), as the derivative of $\lambda\pm$ to n+, corresponds in the one-channel case to the derivative of the absolute value of the gradient in the gradient direction. Altogether DS(p; n_+) is a form that is based on the second directional derivatives of the image function. The edge points, which were defined as the maximum points of the first derivative of the image function, are represented in DS(p; n_+) by zeros (or zero-crossings in the digital grid). For the detection of these zero-crossings (with regard to, for example, a four- or eight-neighborhood), neighboring function values with different signs must be sought. The sign of DS(p; n_+) is, until now, not uniquely defined. The definition of n_+ of the eigenvector of a matrix results in the fact that it is not certain whether n+ or ($-n_+$) is the sought-after vector. Since n_+ cubically rises in DS(p; n_+), DS(p; n_+) is directly dependent on the sign of n_+. For the solution of this problem, Cumani [4] recommends an investigation into the sub pixel domain using a bilinear interpolation. Alshatti and Lambert [1] propose a modification of Cumani's technique. Since λ_+ is an eigen value of the matrix A, the associated eigenvector n_+ can be directly determined. Thereby the complex approximation in the sub pixel domain, as suggested by Cumani, is avoided. The computationally costly calculations of the partial derivatives of K, F, and H to x and y can be accomplished more efficiently if these derivatives are determined directly, without first calculating and storing K, F, and H [14].However, it must still be specified how the partial derivatives of the image functions are to be determined. Alshatti and Lambert [1] and Cumani [4] applied several 3 × 3 convolution masks for this. From [15] it is well known that the use of convolution masks of a fixed size of 3 × 3 pixels is not suitable for the complex problem of determining discontinuities in image functions. Therefore, for the determination of the partial derivatives, masks that are based on the 2-D Gaussian function and their partial derivatives are suggested here. These masks are called "Gaussian masks" and can be parameterized by the standard deviation σ . The size of the Gaussian masks can be specified by those function values that are, e.g., larger than 0.1% of the maximum function value of the Gaussian function for a standard deviation σ . Thus, the choice of a standard deviation of, e.g., σ = 0.5 corresponds to a mask of size 3 × 3 pixels. Large Gaussian masks can be effectively approximated by cascaded block filters with very high efficiency (a few operations per pixel). Note that the Cumani operator can be parameterized over the standard deviation σ if Gaussian masks are included in the calculations of the partial derivatives. Therefore, an application of this operator is also possible in different resolutions [14]. The use of Gaussian masks is, however, not entirely necessary here for the scalability of the operator. Other functions, such as Gabor functions, can be used as well.

5. Proposed Work

Image processing has been under focus since long, lot of study and work has been done in this field, a variety of techniques and algorithms have emerged in the process. A large number of powerful and effective techniques exist for edge detection in digital images. But sometimes our image in not clear, it's blurred. All edge detection algorithms are not able to process such blurred images. For such images De-blurring Edge Detection algorithms come into picture. Proposed work: Various techniques for edge detection in color images were presented previously. The following will cover how significant the differences are in the results when differing techniques for edge detection are applied. A discussion of several criteria for the evaluation of edge operators (in gray-level images) can be found in [21]. The topic of edge detection in color images is, however, not covered there. The results of an investigation [12] of different color variants of the Canny operator have already been described. Here, resulting images for the vector-valued variants of the Canny operator are presented. The results for a selected color test image obtained with the Cumani operator, including Gaussian masks, are compared directly to these results. In addition, a result image with a monochromatic technique is visualized. For a monochromatic-based technique, the classic Mexican hat operator (Log operator) was selected as an example. The Mexican hat operator is defined by the negative Laplacian derivative of a 2-D Gaussian distribution $-\nabla^2\mathrm{GAUSS}(x, y)$ [15]. It holds that

$$-\nabla^2\mathrm{GAUSS}(x, y) = \frac{x^2+y^2-2\sigma^2}{2\sigma^6\Pi}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \qquad (8)$$

The operator can be parameterized with the standard deviation σ. The size of the convolution masks was fixed by those function values that are greater than 0.1% of the maximum function value of the Gaussian function for a standard deviation σ. The convolution mask designed for a selected σ is applied to all three spectral transmissions of the color image. A pixel in a color image is declared as part of a color edge if a zero-crossing was detected in at least one of the resulting images achieved in this manner. In Figure 3, some results of color edge detection for a selected color image "block" are represented. The results can be interpreted as follows. Many pixels in the image background are determined as edge points by applying the monochromatic-based color variant of the Mexican hat operator [see Figure 3(d)]. In addition, many gaps develop at the same time in the detected edges. The results of the Mexican hat operator can be improved by defining a larger standard deviation. In Figure 3, the result for the standard deviation σ = 1.0 was selected in order to show such a comparison to the Cumani operator, which was parameterized over the same value for the standard deviation. Better results are achieved with the Cumani operator [see Figure 3(c) and (e)]. Here, the quality of the results is continually improved if Gaussian masks with a greater standard deviation are used instead of a 3 × 3 convolution mask w σ=0.5.

5.1 Classification of Edges

In addition to quantitative and qualitative advantages of color edge detection, color information allows for physical classification of the edges. The main goal of the following is to give a general overview on various edge classification techniques and to familiarize the reader with the dichromatic reflections model that is commonly applied in physics-based color image processing. Edges in images can have completely different causes due to the geometrical and photometric conditions within a scene. Different types of edges are outlined in Figure 4. Edges can be distinguished into the following five classes:

- Object edges, or orientation edges, arise from a discontinuity of the vector normal of a continuous surface.
- Reflectance edges arise from a discontinuity of the reflectance of object surfaces, for example, by a change of surface material.
- Illumination edges, or shadow edges, arise from a discontinuity of the intensity of the incident lighting. Specular edges, or highlight edges, arise from a special orientation between the light source, the object surface, and the observer and are due to material properties
- Occlusion edges are boundaries between an object and the background as seen by the observer. Occlusion edges do not represent a physical discontinuity in the scène. They exist due to a special viewing position. In many areas of digital image processing, a classification of edges is necessary and/or advantageous. For example, only orientation edges, reflectance edges, and illumination edges should be matched in stereo vision. Specular edges and occlusion edges should not be matched because their occurrence in the image depends on the viewing position

of both cameras, and they do not represent the identical physical locus in the scene. Illumination edges should not be matched if motion analysis is applied. The classification of edges by their physical origin is difficult or even impossible in gray-level images.

6. Result and Discussion

A comparison of the results, which the Cumani operator supplies for the color image “block” [see Figure 3(e)] and for the corresponding gray-level image [see Figure 3(f)], is interesting. It is to be noted that several edges that had not been determined in the gray-level image were detected in the color image. Further investigations have shown that edge detection in color images is more robust in relation to noise than appropriate edge detection in the associated gray-level image. This applies especially to low contrasted images. From the results obtained with the Canny operator, it can also be recognized that some edges could be detected in the color image [see Figure 3(g)] that were not determined in the gray-level image [see Figure 3(h)]. This statement applies likewise to the color image Lena, for which a gray-level representation and the results obtained with the Canny operator were indicated in Figure 1. With a comparison of the results for the Cumani operator indicated in Figure 3 and the Canny operator for the color image “block,” one recognizes that more edges were detected with the Cumani operator than with the Canny operator. This statement cannot be generalized, however, and applies only to the results represented in Figure 3. The inclusion of the results that can be obtained with vector-valued ranking operators, as they were described previously, remains the subject of future work. It can be said that the results that are determined in color images are at least as good as or better than the results that are determined in gray-level images. A part from a qualitative evaluation of the results of color edge detection, a quantitative evaluation is also of interest. As a function of the processed image, about 90% of all detected edges are identical in the color image and intensity image [12]. Also of concern during the detection of edges in color images is the detection of the remaining 10% of the edges. It depends on the respective application whether the expenditure is justified for the detection of this additional 10%. In an edge-based stereo analysis, only those edges can be assigned that were also detected in both images. A missing edge that was not detected can lead to a complete misinterpretation within shape reconstruction. Furthermore, the non-detection of an edge also has a deciding influence on the result of an edge-based segmentation process. In the following, it is not our concern to decide whether the additional edges are needed or not. Rather, vector-valued techniques were introduced that make it possible to at least partly detect the remaining edges. In the following, it is shown that color information can be used, under certain conditions, for edge detection.

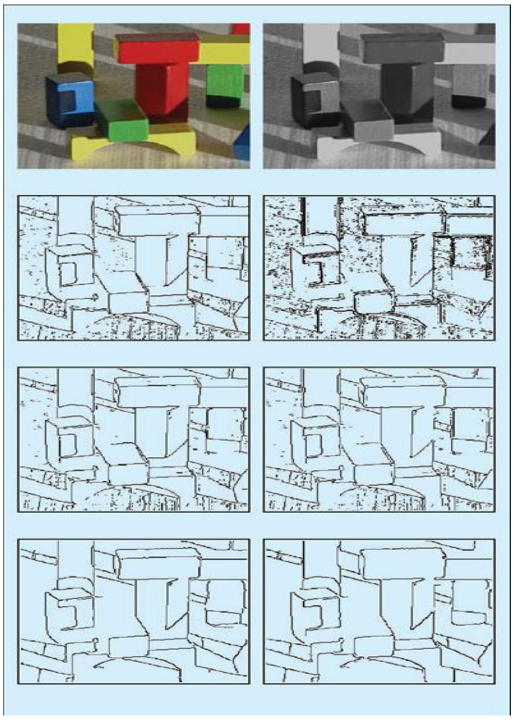

Figure 4: (a) Color image “block” and (b) its gray-level representation. (c) Edge detection results for the Cumani operator with $\sigma = 0.5$, (d) the Mexican hat operator with $\sigma = 1.0$,and (e) the Cumani operator with $\sigma = 1.0$. (f) Results for the graylevel image of “block” for the Cumani operator with $\sigma = 1.0$, (g) the color Canny operator, and (h) the gray-value Canny operator. [Parts (g) and (h) used with permission from John Owens,Stanford University.]

References

[1] W. Alshatti and P. Lambert, “Using eigenvectors of a vector field for deriving a second directional derivative operator for color images,” in *Proc. 5th Int. Conf. Computer Analysis Images and Patterns*, D. Chetverikov, W.G. Kropatsch, eds., 1993, pp. 149–156.

[2] R. Bajcsy, S.W. Lee, and A. Leonardis, “Detection of diffuse and specular interface reflections and inter-reflections by color image segmentation,” *Int. J. Comput. Vis.*, vol. 17, no. 3, pp. 241–272, 1996.

[3] J. Canny, “A computational approach to edge detection,” *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 8, no. 6, pp. 679–698, 1986.

[4] A. Cumani, “Edge detection in multispectral images,” *Comput. Vis. Graph.Image Process.: Graphical Models Image Processing*, vol. 53, no. 1, pp. 40–51,1991.

[5] G. Finlayson, S. Hordley, and M. Drew, “Removing shadows from images using Retinex,” in *Proc. Color Imaging Conf.*, 2002, pp. 73–79.

[6] G. Funka-Lea and R. Bajcsy, “Active color image analysis for recognizing shadows,” in *Proc. 13th Int. Joint Conf. Artificial Intell.*, vol. 2, 1993, pp. 1573–1578.

[7] R. Gershon, A.D. Jepson, and J.K. Tsotsos, “Ambient illumination and the determination of material changes,” in *Physics-Based Vision Principles and Practice: Color*, G.E. Healey, S.A. Shafer, and L.B. Wolff, Eds. Boston, MA: Jones & Bartlett, 1992, pp. 101–108.

[8] T. Gevers and H. Stokman, “Classifying color edges in video into shadow-geometry, highlight, or material edges,” *IEEE Trans. Multimedia*, vol. 5, no. 2, pp. 237–243, 2003.
[9] R.M. Haralick, S.R. Sternberg, and X. Zhuang, “Image analysis using mathematical morphology,” *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 9, no. 4, pp.532–550, 1987.
[10] J.-W. Hsieh, W.-F. Hu, C.-J. Chang, and Y.-S. Chen, “Shadow elimination for effective moving object detection by Gaussian shadow modeling,” *Image Vis. Comput.*, vol. 21, no. 6, pp. 505–516, 2003.
[11] T.L. Huntsberger and M.F. Descalzi, “Color edge detection,” *Pattern Recognit. Lett.*, vol. 3, no. 3, pp. 205–209, 1985.
[12] T. Kanade, “Image understanding research at CMU,” in *Proc. Image Understanding Workshop*, vol. II, 1987, pp. 32–40.
[13] G.J. Klinker, S.A. Shafer, and T. Kanade, “A physical approach to color image understanding,” *Int. J. Comput. Vis.*, vol. 4, no. 1, pp. 7–38, 1990.
[14] A. Koschan, “A comparative study on color edge detection,” in *Proc. 2nd Asian Conf. Comput. Vis.*, vol. III, 1995, pp. 574–578.
[15] D. Marr and E. Hildreth, “Theory of edge detection,” *Proc. Royal Soc. London*, vol. B207, pp. 187–217, 1980.
[16] B.A. Maxwell and S.A. Shafer, “Physics-based segmentation of complex objects using multiple hypotheses of image formation,” *Comput. Vis. Image Understanding*, vol. 65, no. 2, pp. 269–295, 1997.
[17] M. Pietikäinen and D. Harwood, “Edge information in color images based on histograms of differences,” in *Proc. Int. Conf. Pattern Recognit.*, Paris, France, 1986, pp. 594–596.
[18] A. Prati, R. Cucchiara, I. Mikic, and M.M. Trivedi, “Analysis and detection of shadows in video streams: A comparative evaluation,” in *Proc. Int. Conf. Computer Vion and Pattern Recognition*, vol. II, 2001, pp. 571–576.
[19] G.S. Robinson, “Color edge detection,” in *Proc. SPIE Symp. Advances Image Transmission Techniques*, vol. 87, 1976, pp. 126–133.
[20] J.M. Rubin and W.A. Richards, “Color vision and image intensities: When are changes material?,” *Biol. Cybern.*, vol. 45, no. 3, pp. 215–226, 1982.
[21] M. Salotti, F. Bellet, and C. Garbay, “Evaluation of edge detectors: Critics and proposal,” in *Proc. Workshop Performance Characteristics Vision Algorithms*, H.I. Christensen, W. Förstner, C.B. Madson, eds., 1996 [Online]. Available: http://www.vision.auc.dk/~hic/perf-proc.html.
[22] K. Schlüns and A. Koschan, “Global and local highlight analysis in color images,” in *Proc. 1st Int. Conf. Color Graphics Image Processing*, 2000, pp. 300–304.
[23] S.A. Shafer, “Using color to separate reflection components,” *COLOR Res. Applicat.*, vol. 10, pp. 210–218, 1985.
[24] J.C. Solinsky, “The use of color in machine edge detection,” in *Proc.VISION’85*, pp. 4-34–4-52, 1985.
[25] H. Tao and T. Huang, “Color image edge detection using cluster analysis,” in *Proc Int’l Conf. Image Processing*, Washington, D.C., 1997, vol. I, pp. 834–837.
[26] F. Tong and B.V. Funt, “Specularity removal for shape from shading,” in *Proc. Vision Interface Conf.*, pp. 98–103, 1988.
[27] P.W. Trahanias and A.N. Venetsanopoulos, “Color edge detectors based on multivariate ordering,” *Proc. SPIE Visual Communications Image Processing*, vol. 1818, 1992, pp. 1396–1407.
[28] P.W. Trahanias and A.N. Venetsanopoulos, “Color edge detection using vector order statistics,” *IEEE Trans. Image Processing*, vol. 2, no. 2, pp. 259–264, 1993.