Color Edge Detector with Sobel-PCA

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ABSTRACT
Edge detection is one of the most commonly used operations in computer vision, The key of edge detection is the choice of threshold; the choice of threshold directly determines the results of edge detection. How to automatically determine an optimal threshold is one of difficult points of edge detection.

In this paper, Sobel edge detection operator and its improved algorithm are first discussed in term of optimal thresholding. We include color information into a color edge detection approach based on principal components analysis (PCA).

Finally, the edge detection experiments of synthetic image and real color images are conducted by means of two algorithms. The comparative experiment results show that the new algorithm is very effective. The results are also better than the classical methods.

Keywords
Color Edge Detection, Principal Component Analysis, Sobel filter, the first Global Measure of Coherence (GMC1)

1. INTRODUCTION
Edge detection [8,7] is a very important area in the field of Computer Vision. Edges define the boundaries between regions in an image, which helps with segmentation and object recognition. They can show where shadows fall in an image or any other distinct change in the intensity of an image. Edge detection is a fundamental of low-level image processing and good edges are necessary for higher level processing. [1]

The problem is that in general edge detectors behave very poorly. While their behaviour may fall within tolerances in specific situations, in general edge detectors have difficulty adapting to different situations. The quality of edge detection is highly dependent on lighting conditions, the presence of objects of similar intensities, density of edges in the scene, and noise. While each of these problems can be handled by adjusting certain values in the edge detector and changing the threshold value for what is considered an edge, no good method has been determined for automatically setting these values, so they must be manually changed by an operator each time the detector is run with a different set of data.

In this work, the color edge detector is calculated by convolving image frame with the 3x3 Sobel Operator. The reason for choosing the Sobel Operator for gradient calculation is its low computational complexity and fair performance in finding edges. We include color information into a color edge detection approach based on principal components analysis (PCA) [5,6]. this approach has been tested on synthetic image and real color images and the results are satisfactory.

2. EDGE DETECTOR
Generally, an edge detection method [9,10,11] can be divided into three stages. In the first stage, a noise reduction process is performed. In order to gain better performance of edge detection, image noise should be reduced as much as possible. This noise reduction is usually achieved by performing a low-pass filter because the additive noise is normally a high-frequency signal. However, the edges can possibly be removed at the same time because they are also high-frequency signals. Hence, a parameter is commonly used to make the best trade-off between noise reduction and edges information preservation. In the second stage, a high-pass filter such as a differential operator is usually employed to find the edges. In the last stage, an edge localization process is performed to identify the genuine edges, which are distinguished from those similar responses caused by noise. Thresholding techniques may be used to accomplish this process [2,8].

A variety of approaches for edge detection have been proposed for different purposes in different applications. Among the earliest works of edge detection are Sobel, Prewitt, Roberts, and Laplacian edge detectors, all of which use convolution masks to approximate the first or second derivative of an image [2,3].

2.1 Sobel Operator
Sobel operator [13] is formed by two convolution kernels which shows in Figure1. In image processing, these two kernels are used to convolute each point of the image.

Sobel horizon operator

-1	-2	-1
0	0	0
1	2	1

Sobel vertical operator

-1	0	1
-2	0	2
-1	0	1

Fig 1:Sobel convolution kernels

These kernels are designed to respond maximally to edges running vertically and horizontally relative to the pixel grid, one kernel for each of the two perpendicular orientations. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (call these Gx and Gy). These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient. The gradient magnitude is given by:

$$|G| = \sqrt{G_x{}^2 + G_y{}^2}$$

Typically, an approximate magnitude is computed using:

$$|G| = |G_x| + |G_y| \qquad (2)$$

which is much faster to compute.

2.2 Global Measures of Coherence

In this section, we introduce the First Global measures of coherence [4]. This measure is derived from a constraint on the edges in the scene.

We mention a couple that do not require knowledge of the orientations of the edges, but otherwise do not discuss the numerous alternatives. As input to compute the measures, we assume the edge detector has yielded a set of edges:

$$E = \{e_i = (x_i, y_i, \theta_i) | i = 1,...,\text{n}\},$$

Where n is the number of edges. We assume that the ith edge $e_i = (x_i, y_i, \theta_i)$ passes through the point (xi, yi) in the image, and the normal to this edge makes an angle θ_i, with the positive y-axis.

2.2.1 All Edges are Co-Linear

The first constraint is that all of the edges are co-linear [4]. Such a scene can be constructed by placing a convex polygonal object with uniform reflectance in front of a perfectly black background. If an image of such a scene is cropped so that only one depth or surface normal discontinuity is visible, all of the edges will be co-linear. See Figure 2 for an example image of such a scene.

Fig 1 : Cropped regions exhibiting the constraints all Edges are co-linear,

Given one of the edges $e_i = (x_i, y_i, \theta_i) \in E$ it is possible to estimate the line that all of the edges lie on. In the projective geometric notation of [7,8], the representation of this line is:

$$\begin{aligned} L_i &= \left(l_i^1, l_i^2, l_i^3\right)^T \\ &= (x_i, y_i, 1)^T \wedge (x_i + \cos\theta_i, y_i + \sin\theta_i, 1)^T \\ &= (-\sin\theta_i, \cos\theta_i, x_i \sin\theta_i - y_i \cos\theta_i)^T \end{aligned} \qquad (3)$$

We would like to use the sum of the variances of the three line coordinates as the basis for the first measure. A natural question, however, is: how should the three components be weighted? Since the natural use of L, is to test whether a point x = (x, y, 1) lies on the line using x.Li, = 0, a sensible choice for the ratio of the weights is: $(E_x)^2 : (E_y)^2 : 1,$

Where Ex: denotes the expected value of x and Ey denotes the expected value of y. To avoid any dependence on the distance units, we define the first global measure of coherence to be:

$$GMC_1 = \frac{1}{E_x.E_y}\left[(E_x)^2.\sigma^2(l^1) + (E_y)^2.\sigma^2(l^2) + \right. \qquad (4)$$

Where for k = 1, 2, 3

$$\sigma^2(l^k) = \frac{1}{n}\sum_{i=1}^{n}\left[l_i^k - \frac{1}{n}\sum_{j=1}^{n} l_j^k\right]^2 \qquad (5)$$

is the variance of the kth coordinate of Li. There are several ways that Ex and Ey could be estimated. We define:

$$\text{E}_x = \frac{1}{n}\sum_{i=1}^{n}|x_i| \qquad (6)$$

and similarly for Ey.

For evaluation the algorithm color edge detector results we use the First Global measures of coherence (GMC1) [4].

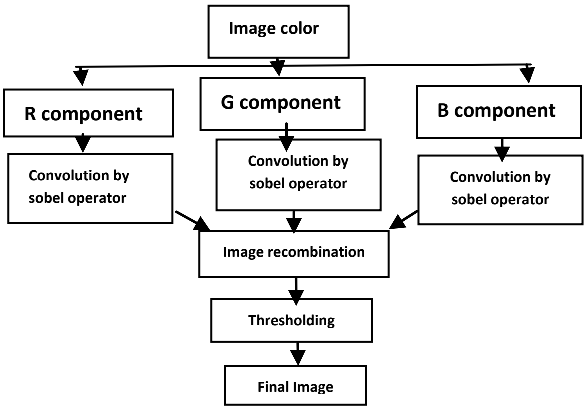
3. PROPOSED APPROACHES

The advantage of Sobel edge operator is its smoothing effect to the random noises in the image. And because it is the differential separated by two rows or two columns, so the edge elements on both sides have been enhanced and make the edge seems thick and bright. Sobel operator is a gradient operator. The first derivative of a digital image is based on a variety of two-dimensional gradient approximation, and generates a peak on the first derivative of the image, or generates a zero-crossing point on the second derivative. Therefore this paper combines the Sobel operator and the principal components analysis (PCA) for reduce color space [5]. The core idea of the algorithm divided in two methods:

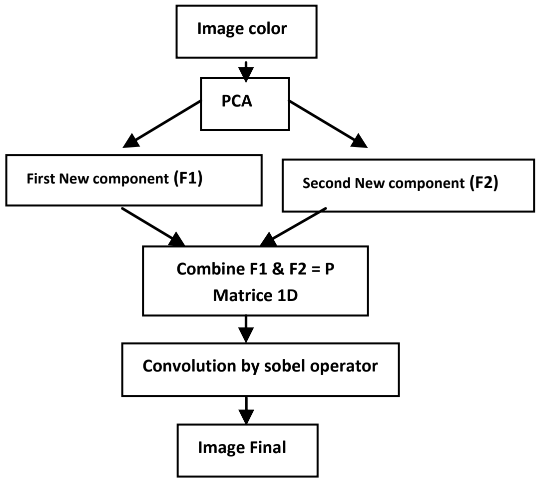
1. Sobel operator:

The algorithm we used for applying colors to the sobel detector was a very simple one:

1. Read color image and divide it into its three separate color channels.
2. Run each color channel by sobel detector separately to find a resulting colored convolution map.
3. Recombine the resulting convolution maps from each of the three color channels into one complete edge map. For this step there are a variety of ways you can combine the edges found for each different.
4. Finally, we added a Thresholding technique



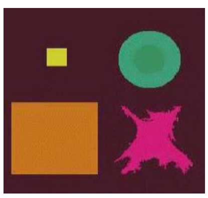
2. *Sobel-PCA operator:*



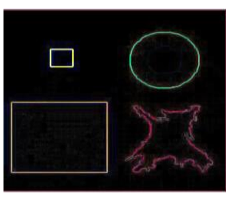
4. EXPERIMENTAL RESULTS

This section, we present the experimentation results of Color edge detection approach based on principal Components analysis (PCA) Using the sobel operator. We compare the performances of the two methods defined above with the First Global measure of coherence [4]. We have underlined the influence of the color space (RGB) and our approach results., we have proposed to use PCA Method for reduce the number of components instead of three components we have only two components, we compare the difference between two methods through calcule of the first global measure of coherence (GMC1) for the color image and varying the Threshold.

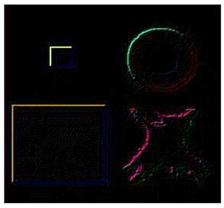
4.1 Results on Synthetic Image



Original image



Sobel- PCA Operator



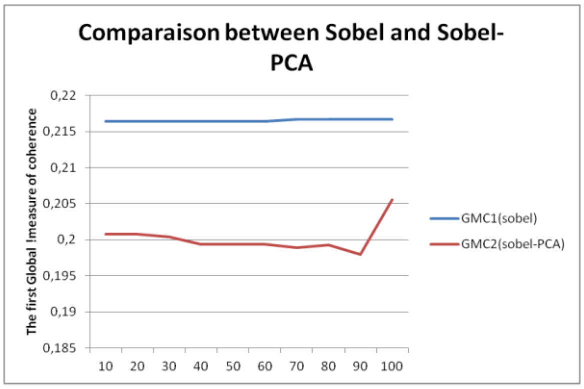
Sobel operator

Fig 2 : the synthetic image

The value of GMC1 form (Sobel) and (Sobel-PCA) with varying the Threshold.

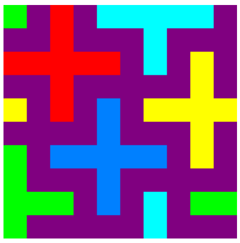
Table1: Resultat of synthetic image

	10	20	30	40	50	60	70	80	90	100
GMC1 (sobel)	0,2164	0,2164	0,2164	0,2164	0,2164	0,2164	0,2167	0,2167	0,2167	0,2167
GMC2 (sobel-PCA)	0,2008	0,2008	0,2004	0,1994	0,1994	0,1994	0,1989	0,1993	0,198	0,2056

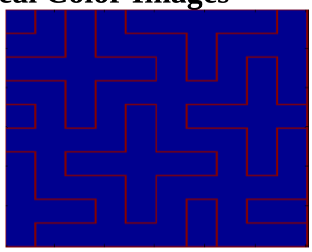


Graph 1: Plots of the first measure of coherence in Synthetic image

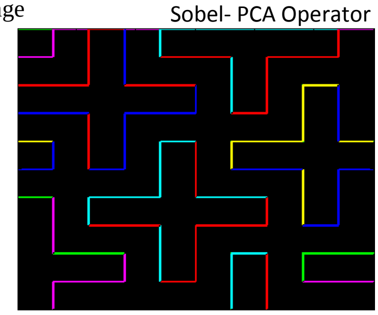
4.2 Results on Real Color Images



Original image



Sobel- PCA Operator



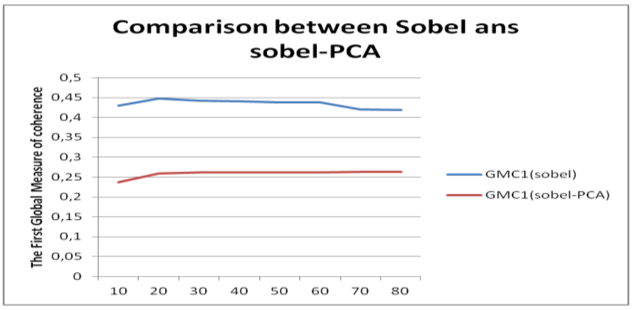
Sobel operator

Fig 4 : Real color images

The value of GMC1 form (Sobel) and (Sobel-PCA) with varying the Threshold.

Table2: Resultat of color image

	10	20	30	40	50	60	70	80
GMC1 (sobel)	0,4292	0,4473	0,4423	0,4403	0,4384	0,4384	0,4199	0,4188
GMC1 (sobel-PCA)	0,2364	0,2584	0,2615	0,2621	0,262	0,2622	0,2628	0,263



Graph 2: Plots of the first measure of coherence in Real color images

These plots were obtained by varying the thresholds inherent in the detectors based on Principal Component analysis (PCA) and RGB color space. The dotted curve lies below the solid one and hence represents superior performance for Components analysis (PCA) relative RGB color space. The effect of the Sobel-PCA is much better then Sobel operator.

5. CONCLUSION

This paper extends existing Sobel operator and presents a new operator Sobel-PCA for Color edge detection description. The feasibility and effective-ness of using this operator is investigated. The results demonstrate that Sobel-PCA significantly outperforms Sobel standard with various thresholding.

6. REFERENCES

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