A Novel Multispectral Lab-depth based Edge Detector for Color Images with Occluded Objects

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Abstract: This paper presents a new method for edge detection based on both Lab color and depth images. The principal challenge of multispectral edge detection consists of integrating different information into one meaningful result, without requiring empirical parameters. Our method combines the Lab color channels and depth information in a well-posed way using the Jacobian matrix. Unlike classical multi-spectral edge detection methods using depth information, our method does not use empirical parameters. Thus, it is quite straightforward and efficient. Experiments have been carried out on Middlebury stereo dataset (Scharstein and Szeliski, 2003; Scharstein and Pal, 2007; Hirschmuller and Scharstein, 2007) and several selected challenging images (Rosenman, 2016; lightfieldgroup, 2016). Experimental results show that the proposed method outperforms recent relevant state-of-the-art methods.

1 INTRODUCTION

Edge detection is one of the most prominent problems in the field of image processing (Zhang et al., 2016; Saurabh et al., 2014; Silberman et al., 2014). It has an important role in many computer vision algorithms and is considered as a fundamental and crucial step particularly for segmentation, feature extraction and object recognition. In order to perform a good edge detection, one should tackle several challenges: variability of illumination, occlusions, density of edges in the scene and noises (Nadernejad et al., 2008). Based on the type of the image, we can identify three categories of methods for edge detection: grayscale image edge detection, color image edge detection and Color-Depth image edge detection (Zhang et al., 2016).

In this paper, we present a novel method for edge detection by combining both color information and depth information in well-posed way without using empirical parameters. First, we apply on color image the L_0 gadient algorithm in order to suppress noises, while preserving important edges (Xu et al., 2011). Second, we compute the first derivative for each image component (Lab colors and Depth information). More precisely, for each pixel of a multispectral image, we form a Jacobian matrix by using the first derivatives. Then, for each pixel, in order to tease out the pairwise relations of the columns of the proposed Jacobian matrix, we perform product of this latter and its transpose. Last, we select the maximal Eigen value of the resulting matrix as edge information. The main advantage of our method is that we do not use empirical parameters and that is a quite straightforward efficient method. Our proposed approach has been compared to both Isola et al. (Isola et al., 2014) and Asif et al. (Asif et al., 2016). These two methods were chosen because they twin multi channels into one meaningful result, as the principle of our method. The approach has been validated on Middlebury stereo dataset (Scharstein and Szeliski, 2003; Scharstein and Pal, 2007; Hirschmuller and Scharstein, 2007) and several selected challenging images (lightfieldgroup, 2016; Rosenman, 2016).

The remaining of this paper is organized as follows. The next section 2 overviews the state-of-the-art for edge detectors. Section 3 describes the proposed method in details. Experimental protocol and results are presented and discussed in section 4. Finally, section 5 concludes this work by overviewing the contribution and pointing out issues for future development.

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2 RELATED WORK

An edge can be described as an acute change in luminosity. Through the past years, many researchers have concentrated on implementing algorithms for grayscale images in order to detect edges effectively. These approaches are classified into two broad categories: (i) Gradient based edge detection and (ii) Laplacian based edge detection. In a gradient based edge detection, one looks for the extrema in the first order derivative of the image to find edges. Several methods have been developed, such as, the Sobel operator (Sobel, 1970),Prewitt operator (Prewitt, 1970), Roberts operator (Roberts, 1963) and Krish operator (Krish, 1970). These classical operators are characterized by their simplicity. Also, because of the approximation of gradient magnitude, the detection of edges and their orientations is simple. However, these operators are sensitive to the noise. In fact, very high noise will degrade the magnitude of the edges which will most probably decrease the accuracy of edge detection. Concerning the Laplacian based edge detection, one searches for zero crossings in the second order derivative of the image to find edges. A set of algorithms have been implemented like Laplacian of Gaussian (LoG) (Marr and Hildreth, 1980) and Difference of Gaussian (DoG) (Davidson and Abramowitz, 1998). Methods of this category are able to find the correct places of edges and their orientations, but they fail at the corners, curves and where the gray level pixel intensity varies due to illumination changes.

Since then, some other refined algorithms have been developed to overcome these limitations, such as, the Canny edge detector (Canny, 1986) which performs a better detection performance under noisy conditions. Actually, Canny's algorithm has the advantages of finding the best error rate, in order to detect edges efficiently. Although the canny edge detector is one of the most widely used edge detectors, it suffers from some drawbacks which include missing edge's junctions. With the use of Gaussian kernel in order to reduce the noise signal, the localization of edges is harder and inaccurate (Perez and Dennis, 1997). Cannyś method is also a high time consuming detector. Moreover, it requires setting threshold values adaptively for each image scene.

To improve the accuracy of edge detection, several researches have already used color image for complex situations because it provides more information compared to the grayscale image (monochromatic image). According to Novack and Shafer (Novack and Shafer, 1987), 90% of edge information in color images can be found as well as in grayscale images. However, the remaining 10% may be important in certain computer vision tasks like image segmentation and image restoration. Thus, authors are convinced that by analyzing the color information, the efficiency and the performance of edge detectors will be improved. For instance, Isola et al.(Isola et al., 2014) proposed to detect boundaries through the use of a statistical association based on pointwise mutual information (PMI). By using pixel color and variance information, authors achieve a good contour detection results. Xin et al.(Xin et al., 2012) presented a revised version of Canny algorithm for color images. This approach involves the concept of quaternion weighted average filter and whole vector analysis. These algorithms have shown better results than the gray level image processing method. Using color information, the algorithm balances between noise elimination and edge preservation. Also, Xu et al. (Chen et al., 2012) introduced a novel multispectral image edge detection algorithm. According to authors, a multispectral image can be well expressed via Clifford algebra which is so suitable for processing multidimensional data. The solution consists of computing a Clifford gradient using the RGB channels. Then through the Clifford differentiation method applied at each point and comparing to its neighbor points, authors determine whether it is an edge point using a chosen threshold. Although these methods provided an efficient detection of the objects in the scene, they usually failed in complex situations (e.g. stacked or occluded objects). They were unable to differentiate between occluded objects having same color. Thus, the boundaries of these objects will be hardly extracted. Obviously, in this case, using only color information will be insufficient.

With the development of image acquisition devices, depth information can now be easily extracted. Depth information is becoming more popular and more interesting to deal with occluded objects. In fact, the algorithms of edge detection based on color information paired with depth information has shown excellent results of edge detection and differentiation notably for same occluded objects. Among the most recent relevant RGB-D edge detection algorithms, we can mention the work of Asif et al. (Asif et al., 2016), where the authors have presented a novel object segmentation approach for highly complex indoor scenes. The solution starts with an initial segmentation step which consists of partitioning the scene into distinct regions. For this purpose, based on color-depth image, authors generated a single multi-scale oriented gradient signal. This latter is a linear combination of oriented gradients determined independently from six channels: three components of Lab color space, depth information, surface normal and surface curvature maps of the scene. After that, authors applied a penalization step on this boundary response by fixing a user-selected threshold to suppress false boundary responses. The proposed approach improves the performance of the segmentation of stacked and occluded objects. However, this method integrates empirical parameters for generating the boundary response which can be seen as a limitation. Also, the selected threshold must be adjusted adaptively for each image. Authors of (Yue et al., 2013) presented a RGB-D based edge detection solution that combined both color data and depth data. First, authors applied Canny edge detector separately to both color and depth images in order to extract color-edges image and depth-edges image. Second, optimized depth-edges also, are retrieved by optimizing the depth-edges using the original color image, and optimized color-edges are computed from the optimization of color-edges, using the original depth image. Last, the final result is formed by fusing both optimized depth-edges image and optimized color-edges image. This approach can easily extract the same color occluded objects. However, the algorithm consists of several time consuming steps.

In order to overcome the aforementioned problems, a novel algorithm is proposed for edge detection by combining both color information and depth information in well-principled way. The main principle of our Lab-D gradient based approach is to integrate different information into one meaningful combination, without requiring empirical parameters for edge enhancement. That's why, we mixed all channels into a Jacobian matrix. Thus, it is quite straightforward and efficient. Results show that the proposed method outperforms recent state-of-the-art methods.

3 PROPOSED METHOD

Based on the work of Drewniok (Drewniok, 1994) for the multispectral gradient computation, we present an approach to separate occluded objects using as input color image and depth image of the scene. Our overall edge detection approach can be split into two main steps:

1. Preprocessing step.
2. Performing the gradient-based edge detection in multi-dimensions.

3.1 Preprocessing Step

According to Cheng et al. (Cheng et al., 2001), selecting the best color model affect the quality of detection process. The RGB color space is suitable for color display. But due to the high correlation among the R, G and B components, RGB is considered not good for color scene segmentation or detection. Thus, we choose to use the CIE(l*a*b*) color space instead. Compared to the RGB, CIE(l*a*b*) color space represents color and intensity information more independently and simply. Indeed, CIE(l*a*b*) can measure efficiently a small color difference as this latter can be calculated as the Euclidean distance between two color points. In addition, by modifying simply the output curves in a and b channels, the CIE(l*a*b*) can be used to make accurate color balance corrections, or to adjust the lightness contrast using the L channel. Authors in (Ganesan P. and Rajkumar, 2010) review a segmentation method based on CIE(l*a*b*) color space. The results show that the implementation based on CIE(l*a*b*) outperform other color spaces with various types of noises and using various edge detectors algorithms. So, the CIE(l*a*b*) seems to be a suitable color model for edge detection.

A Lab-D image is composed of pair of images $I_{\text{Color-D}} = (I_{\text{Color}}, I_{\text{Depth}})$, where I_{Color} denotes a traditional three-channel color image (L channel, a channel and b channel) and I_{Depth} denotes depth image (D channel). Since all edge detection results are easily affected by image noise, it is important to filter out any noise to avoid false positives. Usually, in order to smooth I_{Color} images, the Gaussian filter is used. However, when filtering noise using the Gaussian smoothing algorithm, some regions are blurred. Thereby, the associated edges will not be extracted. Xu et al. (Xu et al., 2011) presented a novel algorithm that preserves edges after smoothing process. For this reason, authors used L_0 gradient minimization, which can remove small-magnitude gradient. The method suppressed low-amplitude details. Mean-while it globally optimized the edge detection process. Therefore, the L_0 gradient algorithm is utilized in this paper. The gradient operator ∇ applied to a scalar image function I is defined as follows.

$$\nabla I = \begin{pmatrix} \frac{\partial I}{\partial x} \\ \frac{\partial I}{\partial y} \end{pmatrix}. \tag{1}$$

The idea is that the gradient's direction determines the acute change of intensity, and the gradient's magnitude corresponds to the strength of change. But the gradient operator acts only on scalar functions. This is why we compute the first order Gaussian derivative by the convolution of the image I with the Gaussian function and apply the gradient on them.

$$\begin{aligned} \frac{\partial (I * G)(x,y)}{\partial x \partial y} &= I * \frac{\partial G(x,y)}{\partial x \partial y}, \\ &= \left(I * \frac{\partial G(x,y)}{\partial x} \quad , \quad I * \frac{\partial G(x,y)}{\partial y} \right), \end{aligned} \tag{2}$$

where the 2-D Gaussian function G(x,y) is represented by equation 3:

$$G(x,y) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right). \tag{3}$$

In practice, the convolution is done between the considered image and the convolution masks in both x and y directions. The pair of convolution masks G_x and G_y are computed using equations 4 and 5:

$$G_x = \frac{-x}{2\pi\sigma^4}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right). \tag{4}$$

$$G_y = \frac{-y}{2\pi\sigma^4}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right). \tag{5}$$

3.2 Performing the Gradient-based Edge Detection in Multi-dimensions

In order to take into account all information from color image and depth image, the multi-spectral image function $\overrightarrow{S}(x,y)$ forms a vector of m scalars, where m represents the total of channels derived from $I_{\text{Color-D}}$.

$$\overrightarrow{S}(x,y) = \begin{pmatrix} S_1(x,y) \\ . \\ . \\ . \\ S_m(x,y) \end{pmatrix}. \tag{6}$$

In our method $m = 4$ (three-channels of the I_{Color} and one-channel of I_{Depth}), So:

$$\overrightarrow{S}(x,y) = \begin{pmatrix} I_L(x,y) \\ I_a(x,y) \\ I_b(x,y) \\ I_D(x,y) \end{pmatrix}, \tag{7}$$

where I_L denotes the L channel image, I_a denotes the a channel image, I_b denotes the b channel image and I_D denotes the depth channel image for each component of $\overrightarrow{S}$, we compute separately its Gaussian derivative ∇S_i, where $i \in \{1...m\}$ by applying the equation 2.

$$\begin{aligned}\frac{\partial S_i(x,y)}{\partial x \partial y} &= \left(S_i * G_x \quad , \quad S_i * G_y\right), \\ &= \left(S_{\text{ix}} \quad , \quad S_{\text{iy}}\right).\end{aligned} \tag{8}$$

Then, for each pixel (x,y), we form the Jacobian matrix J with the Gaussian derivatives as shown below:

$$J = \begin{pmatrix} \frac{\partial S_1(x,y)}{\partial x \partial y} \\ . \\ . \\ . \\ \frac{\partial S_m(x,y)}{\partial x \partial y} \end{pmatrix} = \begin{pmatrix} S_{1\text{x}}(x,y) & S_{1\text{y}}(x,y) \\ . & . \\ . & . \\ . & . \\ S_{\text{mx}}(x,y) & S_{\text{my}}(x,y) \end{pmatrix}. \tag{9}$$

In our work, the Jacobian matrix is represented in equation 10 as follows:

$$J = \begin{pmatrix} \frac{\partial I_L(x,y)}{\partial x \partial y} \\ \frac{\partial I_a(x,y)}{\partial x \partial y} \\ \frac{\partial I_b(x,y)}{\partial x \partial y} \\ \frac{\partial I_D(x,y)}{\partial x \partial y} \end{pmatrix} = \begin{pmatrix} I_{\text{Lx}}(x,y) & I_{\text{Ly}}(x,y) \\ I_{\text{ax}}(x,y) & I_{\text{ay}}(x,y) \\ I_{\text{bx}}(x,y) & I_{\text{by}}(x,y) \\ I_{\text{Dx}}(x,y) & I_{\text{Dy}}(x,y) \end{pmatrix}. \tag{10}$$

The multi-spectral gradient approach is then the combination between all the image components derivatives, which have been already illustrated in the Jacobian matrix J, in order to get magnitude and direction of the strongest change at each pixel position. Then, we compute the $J^T J$ matrix to find the best compromise between all image gradient components and to avoid the use of empirical values introduced in (Asif et al., 2016).

$$J^T J = \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix}, \tag{11}$$

where
$g_{11} = S_{1\text{x}}^2 + ... + S_{\text{mx}}^2$,
$g_{22} = S_{1\text{y}}^2 + ... + S_{\text{my}}^2$,
$g_{12} = g_{21} = S_{1\text{x}}S_{1\text{y}} + ... + S_{\text{mx}}S_{\text{my}}$.
In our case, we compute g_{11}, g_{12}, g_{21} and g_{22} as follows:
$g_{11} = I_{\text{Lx}}^2 + I_{\text{ax}}^2 + I_{\text{bx}}^2 + I_{\text{Dx}}^2$,
$g_{22} = I_{\text{Ly}}^2 + I_{\text{ay}}^2 + I_{\text{by}}^2 + I_{\text{Dy}}^2$,
$g_{12} = g_{21} = I_{\text{Lx}}I_{\text{Ly}} + I_{\text{ax}}I_{\text{ay}} + I_{\text{bx}}I_{\text{by}} + I_{\text{Dx}}I_{\text{Dy}}$.
The magnitude and the direction of the strongest change of $\overrightarrow{S}$ corresponds to the greatest eigenvalue and its associated eigenvector of the matrix $J^T J$, respectively. Actually, according to Drewniok (Drewniok, 1994), this extremum can be exploited through the Rayleigh-quotient of the matrix $J^T J$. In fact, this is important since the extremum of the Rayleigh-quotient matrix are found through the eigenvalues of the matrix. As our multispectral function $\overrightarrow{S}$ is defined on two directions x and y, a 2x2 matrix $J^T J$ is found. Then, two eigenvalues λ_1 and λ_2 are calculated for each point (x,y), where $\lambda_{\text{max}} = max(|\lambda_1|, |\lambda_2|)$. Obviously, λ_{max} is given by:

$$\lambda_{\text{max}} = \frac{g_{11} + g_{22}}{2} + \sqrt{g_{12}^2 + \frac{(g_{11} + g_{22})^2}{4}}. \tag{12}$$

The direction φ_{max} can be computed with equation 13:

$$\varphi_{\text{max}} = \frac{1}{2} * \arctan\frac{2 * g_{12}}{g_{11} - g_{22}}. \tag{13}$$

Finally, at this step an edge image is resulted as shown in equation 14:

$$I_{\text{edge}} = \begin{pmatrix} \lambda_{\max}(1,1) & . & . & . & \lambda_{\max}(1,w) \\ . & & . & & . \\ . & & & . & . \\ . & & & & . \\ \lambda_{\max}(h,1) & . & . & . & \lambda_{\max}(h,w) \end{pmatrix}, \tag{14}$$

where h denotes the height of the source image and w denotes the width of the source image.

4 EXPERIMENTAL EVALUATION AND RESULTS

In this section, in order to tease out the advantage of using the depth information, we compare our results with both (Isola et al., 2014; Asif et al., 2016) results. These comparisons are performed on RGB-D images and the results are illustrated in Figure 1 and Table 1.

4.1 Experimental Protocol

Our experimental protocol consists of evaluating our method in terms of edge detection accuracy on stacked and occluded objects. To quantify the performance, we use the publicly available Middlebury stereo dataset (Scharstein and Szeliski, 2003; Scharstein and Pal, 2007; Hirschmuller and Scharstein, 2007). It contains RGB-D images of different scenes, in which a large variety of objects (cones, plastic, lampshades and circles) are stacked and occluded over each other in several complicated layouts and with sometimes same colors. This is a motivating dataset for object detection to separate distinct or same occluded objects. Then, a collection of images with their correspondent depth images (lightfieldgroup, 2016; Rosenman, 2016) contains a variety of images which are characterized by different illumination settings, containing several objects with the same color and evidently occluded. The experiments show that our proposed method, using CIE(l*a*b*) color images and disparity map, is able to effectively handle the occlusion cases in complex scenes with short time consuming. In all experiments, for the L_0 smoothing algorithm, we selected the values $\lambda = 0.005$ and $K = 2.0$.

All methods are tested using the same system with an Intel CORE i5 CPU, 8 GByte RAM and Intel(R) HD Graphics 3000.

4.2 Validation

Here we give details about the configuration that we have used for the relative works. For the method of (Asif et al., 2016), in order to get the best gradient response for each channel (L, a, b or D), three preliminary empirical parameters are setted ($\psi1 = 0.95$, $\psi2 = 0.5$ and $\psi3 = 0.5$). Also, for the penalization step, a user selected threshold δb is asked for every image. In our experiments, when implementing Asif et al. (Asif et al., 2016) method we kept fixed and set to δb = 0.14 for all images. For (Isola et al., 2014), we choose to run experiments for two cases: (i)by only considering color information(Lab channels) as the authors suggested (PMI) and (ii)by considering both color information and depth information too to see what will be changed by adding depth information (PMID).

The Figure 1.(f) illustrates the results of our method compared to selected works (Isola et al., 2014; Asif et al., 2016) on several test images. From this figure, we can clearly notice that the proposed RGB-D gradient based method outperforms significantly the state-of-the-art methods. Moreover, we can see that the salient objects in each image are efficiently detected. Beside this, we can see that object occlusion is perfectly handled and edges has been appeared significantly. In Figure 1.(c), Figure 1.(d) and Figure 1.(e), we can notice that some of edges were not preserved, which were preserved by our technique. To visualize these areas clearly, we have highlighted them with red circles where edge detection was failed on the competent methods. We have also measured the computation time for these approaches. The results are resumed in the Table 1. We have shown in terms of time-consuming that our method works faster than other methods.

4.3 Discussion

In our method, the only parameters used are λ and K for smoothing with the L_0 gradient minimization. After several attempts, we have noticed that $\lambda = 0.005$ and $K = 2.0$ are suitable for most images.

For Asif et al. method (Asif et al., 2016), in order to achieve a good edge detection, we have to choose a user selected threshold parameter δ_b suitable for each image. Also, for Isola et al. method (Isola et al., 2014), several parameters are selected beforehand by authors, such as, ρ (free parameter for optimizing segmentation performance), d (Gaussian distance) and Z (a normalization constant). Experiments show that these parameters affect dramatically the edge detection performance in terms of quality and speed. This is why, we have chosen to propose and implement an unsupervised method which does not depend from any parameter and is computationally adaptive to any type of image. So, for the ex-

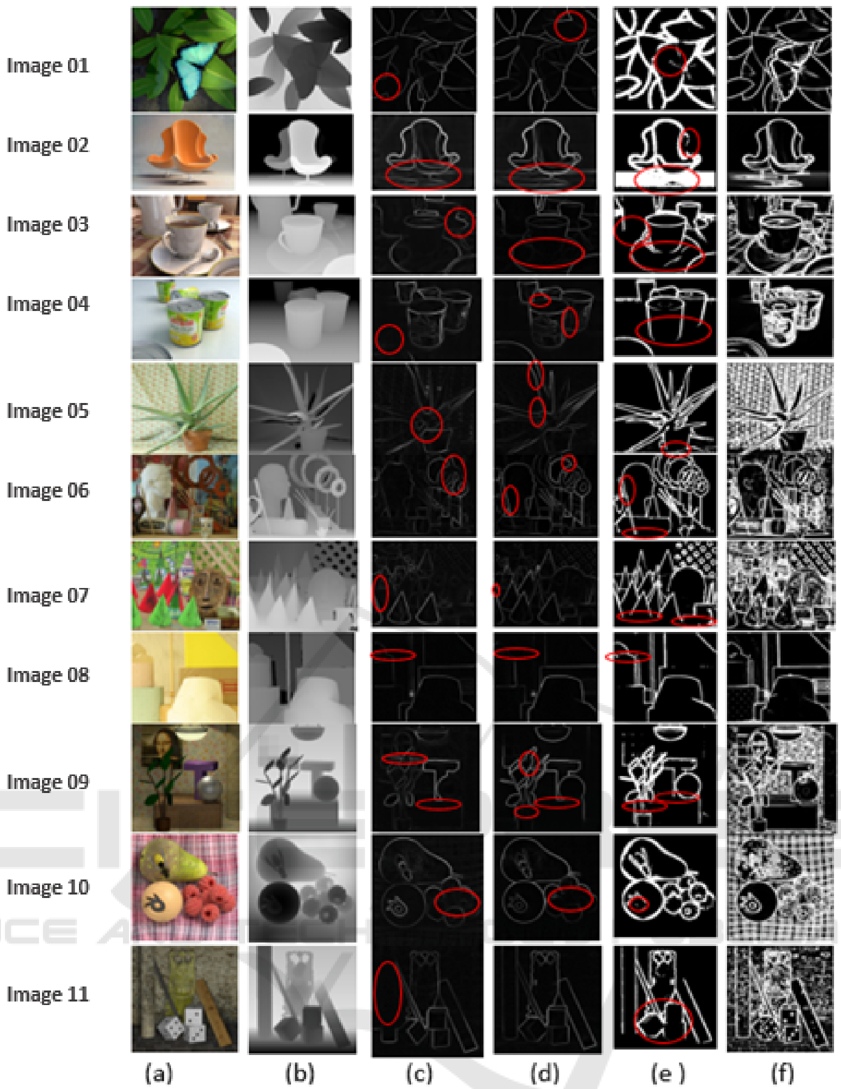

Figure 1: Edge detection results by applying different methods on input images (a) RGB image and (b) depth image. (c) for RGB information and (d) for both combined color and depth images are the results of Isola et al. (Isola et al., 2014). (e) is the result of Asif et al. method (Asif et al., 2016). Finally, (f) represents the results of our method.

traction step of the gradient-based edge detection, we have presented a well-principled edge detection method without using any empirical parameter by assembling different Lab-D image channels into a Jacobian matrix. This method is suitable for all images since we are not supposed to choose any parameter according to each image. Moreover, to reduce the noise in some images (cf. figure1.(f)), we plan to adapt the approach proposed by (Yue et al., 2013) as a post-processing step. The main idea behind this method is to rely on depth information to remove false-positive edges.

5 CONCLUSION

A novel method for edge detection has been proposed. Our method consists of acquiring two images (Lab image and depth image). First of all, we apply the L_0 gradient minimization algorithm on the Lab image in order to suppress noises. Next, we compute the first order gaussian derivative for each channel separately. Then, we assemble these derivatives on a Jacobian matrix. After that, in order to obtain the pairwise relations of the columns of the proposed Jacobian matrix, we perform a product of this latter and

Table 1: Computation time in seconds for different Methods.

Test scene No.	PMI (sec) (Isola et al., 2014)	PMID (sec) (Isola et al., 2014)	Asif et al. method (sec) (Asif et al., 2016)	Our method (sec)
Image 01	3.15	3.07	0.86	**0.539**
Image 02	2.13	2.10	0.576	**0.349**
Image 03	7.68	7.40	1.516	**1.127**
Image 04	7.35	8.12	1.008	**0.883**
Image 05	13.80	13.47	1.536	**1.305**
Image 06	14.70	16.02	1.730	**1.692**
Image 07	14.69	15.27	1.407	**1.253**
Image 08	15.36	13.62	2.008	**1.271**
Image 09	13.44	12.90	1.950	**1.129**
Image 10	12.99	12.90	1.351	**1.251**
Image 11	12.61	12.69	1.370	**1.136**

its transpose. Finally, the maximal Eigen value of the resulting matrix is selected as edge information.

Our main contribution consists of assembling all the components of Lab image and depth image (L,a,b and D) in a well-posed way without requiring any empirical parameters.

Thus, experimental results show an improvement compared to recent state-of-the-art methods (Isola et al., 2014; Asif et al., 2016). In fact, our method distinguishes occluded objects even if they have the same color. Also, our method takes into account even the small details in an image.

As future work, we plan to develop a post-processing step which cleans the resulting image from non-boundary edges, while preserving details as much as possible. We will try to do not use any empirical parameter. Then, we will use this method in a blob detection algorithm.

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