

# Specular reflection detection algorithm for endoscopic images

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## Abstract

Endoscopy is a process that allows viewing/ visualize the inside of a human body. In this article, we propose a specular reflection detection algorithm for endoscopic images that utilizes intensity, saturation and gradient information. The proposed algorithm is a two-stage procedure: (a) image enhancement using an adaptive alpha-rooting algorithm and (b) an efficient reflection detection algorithm in the HSV color space. The extensive computer simulations show a significant improvement over state-of-the-art results for specular reflection detection and segmentation accuracy.

## Introduction

Endoscopy is a process that allows viewing and visualize the inside of a human body. Currently, the doctors use endoscopy to diagnose diseases of the stomach, heart, urinary tract, joints, and abdomen [1].

In most cases, endoscopic images have a specular light reflection (mirror-like) on the surface internal organs. This reflection is described as glossiness and is usually due to the existence of wet over the surface of the organ. These artifacts are sometimes obstructed with the automatic texture analysis and lead to the result of false diagnosis and do not match treatment. The presence of specular highlights can hide the underlying features of a scene within an image and can be problematic in many applications [2,3]. This a challenge for image stitching, computer-aided diagnosis of skin cancers of dermatological images, cervical cancer detection using colposcopy, etc.

Recently, has seen much progress on detection and removing the specular reflections on the endoscopy's images. However, the developed methods worked under certain circumstances, yet the precision of specular separation and vividness after inpainting remain to be improved. Because most of these methods based on objects segmentation and detection and which itself is not solved yet [4].

The proposed algorithm is a two-stage procedure: (a) image enhancement using an adaptive alpha-rooting algorithm and (b) an efficient reflection detection algorithm in the HSV color space. We use the image enhancement procedure for improving the visual appearance of the image and provide "better" transform for future automated detection and segmentation. The basic idea is to apply the modified  $\alpha$ -rooting image enhancement approach for different image blocks and a parameter optimization via the measure of enhancement (EME). For automatic specular reflection detection stage, we use space transformation, binarization processing, and morphology operations.

## Related Work

Specular reflection detection algorithm for endoscopic images can be classified regarding two properties: thresholding and feature-based methods (fig. 1) [5].

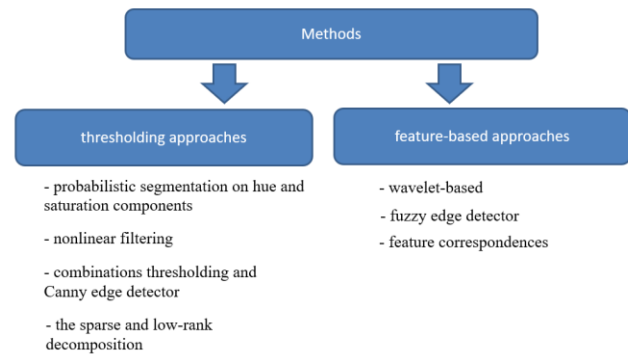


Figure 1. Key specular reflection detection methods classification

The specular detection is the subject in different medical applications have investigated by many researchers. In some cases, the thresholding algorithms show the effectiveness of detecting specular regions [6,7]. Authors in [8] used the thresholding for the saturation and intensity components, that reduce the highlights in laparoscopic surgery. Zimmerman-Moreno et al. proposed to use probabilistic segmentation on hue and saturation components for detection specular regions [9]. The color balance adaptive thresholds and nonlinear filtering allow detecting high intense specular highlights in [10]. The authors in [11] proposed combinations thresholding and Canny edge detector for large and small regions respectively. Stehle et al. used the brightest as the global threshold in the YUV color space. A specular highlights algorithm based on nonlinear filtering and color image thresholding proposed in [6]. To track the 3D beating heart motion in minimally invasive surgeries, authors in [12] and [13] used thresholding, combined with a mask dilation process, to detect specular reflections.

Each of these methods has strong and weak points. The main disadvantages of the known methods come from the fact that most of them are unable to detect large specular reflection regions and are more suitable for the small high intense specular highlights.

So, the weaknesses of traditional methods are:

- extremely sensitive to parameters.
- fails to detect in case a large range of brightness light sources and complex texture organs surface.
- mostly limited to their chosen field of applications and computational complexity.
- unable to detect large specular reflection regions and are more suitable for the small high intense specular highlights.

The objective of our work is to develop a new specular reflection detection algorithm for endoscopic images.

## Proposed detection algorithm

To detect the artifact of specular highlights and reflection in endoscopic images, we developed an automatic solution that we show in Fig. 2. The input is a stream of RGB images from a video decoder connected to the endoscopic camera. We propose a solution to process each image to contrast enhancement based on combined local and global image processing, then detect the specular reflection regions using color space transformation and binarization processing.

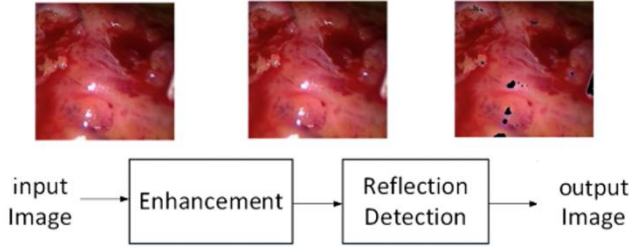


Figure 2. System block diagram

Many medical images may suffer from the following degradations: poor contrast due to poor illumination or finite sensitivity of the imaging device and electronic sensor noise. Image enhancement is the image processing that the results are more suitable for display or further image analysis [14-17]. The solution of the last task is very important when image enhancement procedure is used as a preprocessing step for other image processing techniques such as detection, recognition, and visualization.

We use image enhancement algorithm based on combined local and global image processing (See Algorithm 1) [18].

### Algorithm 1 Image enhancement

**Input:** Original image  $I_{i,j}$

- 1: **for** every blocks size from  $p=8$  to  $64$  **step** 8
- 2:     **for** every parameter from  $\alpha = 0.5$  to  $1$  **step** 0.01
- 3:         **for**  $I_{m,n}$
- 4:             calculate Fourier Transform  $X_{p,s}$
- 5:             calculate  $\hat{X}_{p,s} = X_{p,s} \times |X_{p,s}|^{\alpha-1}$
- 6:             calculate Inverse Fourier Transform  $\hat{I}_{p,s}$
- 7:             calculate  $EME_{k_1,k_2}$
- 8:              $\alpha_{opt} = \max(EME_{k_1,k_2})$
- 9:             calculate  $\hat{X}_{p,s,\alpha_{opt}} = X_{p,s} \times |X_{p,s}|^{\alpha_{opt}-1}$
- 10:         **end**
- 11:     **end**
- 12:     calculate weights  $W_{p,s}$
- 13: **end**
- 14: calculate weighted average  $\tilde{I}(i,j)$

**Output:** Enhanced image  $\tilde{I}(i,j)$

The block diagram of the proposed enhancement algorithm is shown in figure 3. The basic idea is to apply  $\alpha$ -rooting image enhancement approach for different image blocks [19,20]. For every block, we use the transform-based enhancement algorithm base on the  $\alpha$ -rooting and magnitude reduction method [14]:

$$\hat{X}(p,s) = X(p,s) \times |X(p,s)|^{\alpha-1} = |X(p,s)|^\alpha \times e^{i\theta(p,s)},$$

where  $X(p,s)$  is the transform coefficients of the image,  $\alpha$  is a user defined operating parameter,  $\theta(p,s)$  is the phase of the transform coefficients.

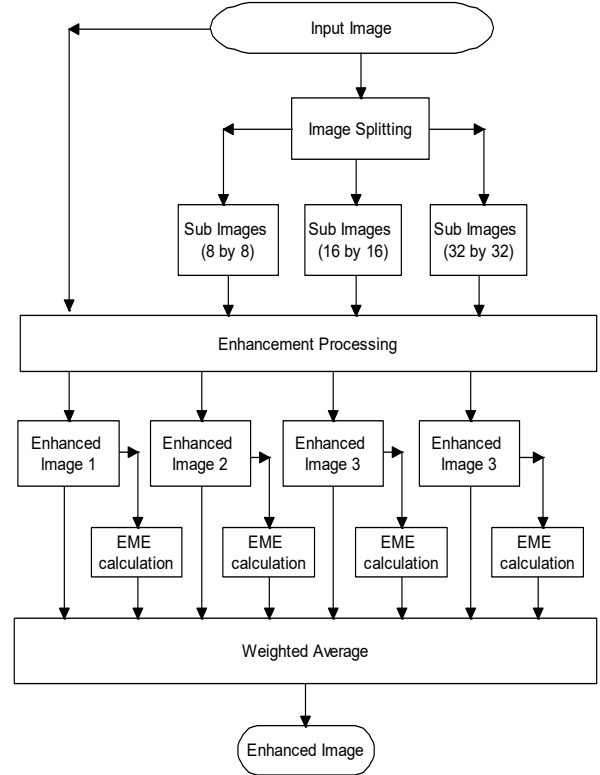


Figure 3. Block diagrams of the proposed algorithm

The  $\alpha$ -rooting transform depends on the parameter  $\alpha$ . We are choosing the best (optimal) enhancement image through optimization of measure enhancement (EME) introduced by Agaian [21]:

$$EME_{k_1,k_2} = \max\left(\frac{1}{k_1 \times k_2} \times \sum_{l=1}^{k_1} \sum_{k=1}^{k_2} 20 \times \log \frac{X_{max;k,l}^\omega}{X_{min;k,l}^\omega}\right),$$

where  $X_{max;k,l}^\omega$  and  $X_{min;k,l}^\omega$  respectively are the minimum and maximum of the image  $x(n,m)$  inside the block  $\omega_{k,l}$ .

For every patch of the image, we apply  $\alpha$ -rooting algorithm with the value of alpha that maximizes the value of EME.

Figure 4 demonstrates the image enhancement results obtained by the proposed algorithm.

A map must be generated that contains ones where the image is undisturbed and zeros where specular reflections occur. The proposed specular reflection detection algorithm shows in Fig. 5. The first part of our solution involves transform from RGB to into the HSV color space by applying the linear transform. The specular highlights are very bright, so the affected pixels show high luminance in the HSV color space. Some results for detections specular reflection in different channels are shows in Table 1. We study RGB, YUV, YIQ, HSV color spaces for this task.

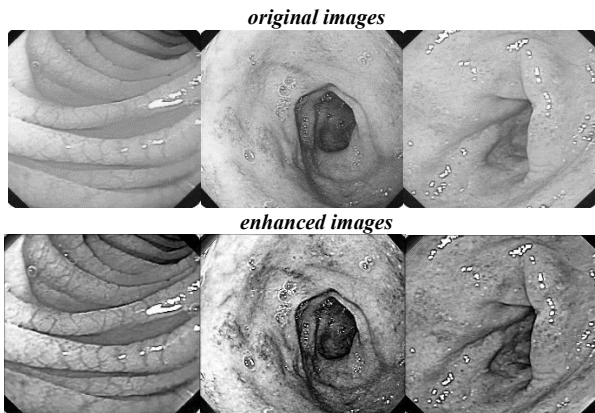


Figure 4. Examples of image enhancement.

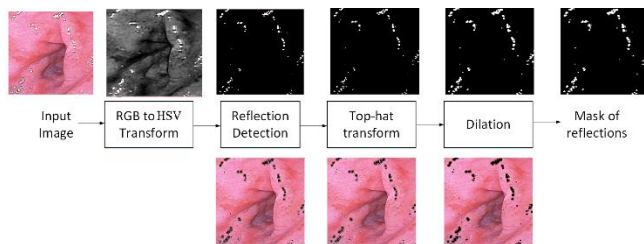


Figure 5. The proposed specular reflection detection algorithm

We chose  $S$ -component in  $HSV$  model to detect large specular reflection regions and the small high intense specular highlights. This color attribute was used because specular highlights are characterized by the local coincidence of intense brightness and unsaturated color.  $HSV$  is alternative representations of the  $RGB$  color model with components Hue, Saturation, Value. This color space mixes the different colors, with the saturation dimension resembling various shades of brightly colored paint, and the value dimension resembling the mixture of those paints with varying amounts of black or white paint. The saturation image shows less false detections of the specular highlights pixel than other components.

Then we perform histogram analysis on a single image to identify suitable intensity and saturation thresholds. For this purpose is to apply the Otsu method with a threshold value equal to 10. The histogram for  $S$ -component with the threshold is shown in Fig. 6.

Since there are often white rings around the affected pixels in the reconstructed image, we reduce the segmented areas by morphological processing. For this purpose, the top-hat transform is applied. This transforms base on the opening operation and returns an image containing those objects that are smaller than the structuring and are brighter than their surroundings. After that, we use the dilation to enlarge detected regions.

The images with detected by the proposed algorithm specular highlight regions presented on Fig. 7. The examples demonstrate the effectiveness of the proposed algorithm.

Table 1. Images in different channels and result of reflection detection

| Color space | Images in different channels and result of reflection detection |          |          |
|-------------|---|----------|----------|
| <b>RGB</b>  | <b>R</b>  | <b>G</b> | <b>B</b> |
|             |   |          |          |
|             |   |          |          |
| <b>YUV</b>  | <b>Y</b>  | <b>U</b> | <b>V</b> |
|             |   |          |          |
|             |   |          |          |
| <b>YIQ</b>  | <b>Y</b>  | <b>I</b> | <b>Q</b> |
|             |   |          |          |
|             |   |          |          |
| <b>HSV</b>  | <b>H</b>  | <b>S</b> | <b>V</b> |
|             |   |          |          |
|             |   |          |          |



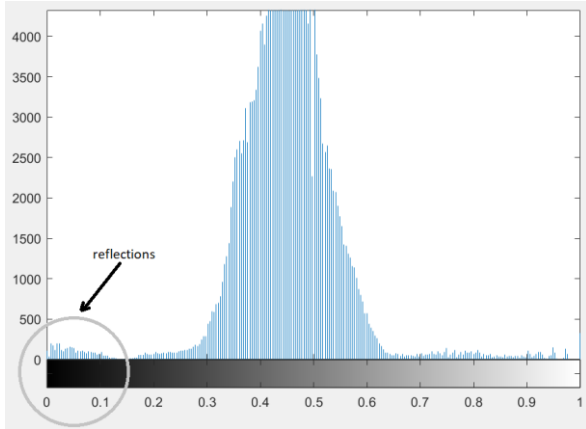


Figure 6. The histogram for S-component

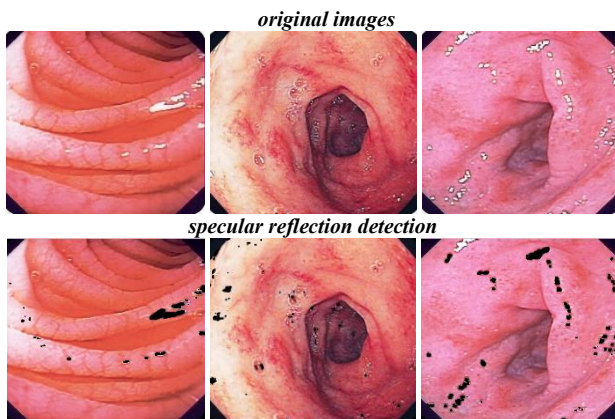


Figure 7. Examples of specular reflection detection

## Experiments

We used 100 images to demonstrate the effectiveness of the proposed method. These images contain data coming from organs with different reflective properties and varying illuminations: abdominal wall, ureter, kidney, and heart. We also received the ground truth for images from our dataset.

To evaluate the effectiveness of the proposed method we use the following metrics:

- The probability of correct detection:

$$Prob.CorrectPrediction = \frac{TP}{NumDefPix}$$

- The probability of a false alarm:

$$Prob.FalseAlarm = \frac{FP}{NumAllPix - NumDefPix}$$

where  $TP$  is true positive,  $FP$  is false positive,  $NumDefPix$  - the number of pixels belonging to the reflection,  $NumAllPix$  - total number of pixels,  $NumUndmgPix$  - the number of pixels not belonging to the reflection.

The experimental results (table 2) show that the probability of correct detection by the proposed method has the highest value. The new approach is better than the existing ones because it is an

adaptive solution in complex cases such as change of appearance or texture.

We compare the proposed specular reflection detection algorithm for endoscopic image and the well-known classical methods [6,9].

**Table 2. Comparison the probability of detection for different methods**

|                      | The probability of false alarm, % | The probability of correct detection, % |
|----------------------|-----------------------------------|---|
| Zimmerman et al. [9] | 24                                | 79                                      |
| Arnold et al. [6]    | 27                                | 82                                      |
| Proposed method      | 5                                 | 86                                      |

## Conclusions

We present a new automatic specular reflection detection algorithm for endoscopic images. The basic idea is to apply the modified alpha-rooting image enhancement approach and an efficient reflection detection algorithm in the HSV color space. The proposed image enhancement results compare favorably against other state-of-the-art approaches.

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