

# Curve based Fast Detail Enhancement for Biomedical Images

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**Abstract:** Biomedical images are widely collected from various applications, which are used for patients' screening, diagnosis and treatment. The dark regions of biomedical images may play an important role as the bright regions. The enhanced details in the dark regions of biomedical images simultaneously maintain the quality of the rest of the images and reveal more information for doctors and surgeons in medical procedures. This paper proposes a fast method to adaptively enhance the details in the dark regions of biomedical images, including X-rays, video frames of laparoscopy in minimally invasive surgery (MIS).

## 1 INTRODUCTION

Biomedical image processing is a broad and complex field. In order to diagnose and treat patients, biomedical images are essential. Low quality and contrast of biomedical images will reduce the doctor's ability to analyze the images, causing subsequent processing difficulties. Moreover, due to medical devices and procedures, doctors may have limited controls in acquiring medical images leaving biomedical images with non-homogeneity of luminance and contrast levels. Hence it is vital to enhance the biomedical image quality as well as improve the image contrast. For instance, X-rays may be low in contrast and details. Frames obtained during minimally invasive surgery may have a large shaded region due to less adequate light introduced into the cavity; dark-colored tissue may lack details in high contrast frames. Then it is essential to recognize images that need enhancement then adaptively select the targeted dark regions for further processing and image contrast enhancement.

Many image enhancement techniques have been developed by researchers including fuzzy set theory image enhancement method (Preethi & Rajeswari, 2013), histogram equalization image enhancement method (Agaian et al., 2007), histogram matching image enhancement method (Irmak & Ertas, 2016) and equalized histogram equalization image enhancement method (Kadhun, 2012). Besides, there

are other image enhancement techniques, such as nonlinear image enhancement technique (Singh et al., 2015; Yaping et al., 2012) and wavelet transform technique (Singh et al., 2015; Premkumar et al., 2014; Ehsani et al. 2011).

Also, in image enhancement, one of the most generally used and essential technique is contrast enhancement. The contrast enhancement's primary purpose is to adjust the local contrast to bring out the image's exact regions. Contrast stretching is a contrast enhancement technique used to extend an image's dynamic range (Zakaria et al., 2010). Other image contrast enhancement methods, including homomorphic filtering (Zakaria et al., 2010), retinex (Chen & Beghdadi, 2010), and histogram equalization (Kim, 1997). Our proposed method is based on histogram equalization. The proposed method consists of two parts: the first part divides images into different intensity regions; the second part will further process the dark regions of the targeted images.

The rest of this paper is organized as follows. Section 2 deals with the previous work of the histogram equalization (HE) methods. Section 3 presents our proposed curve based fast detail enhancement method. The experiment results are shown in section 4, and section 5 gives the conclusion of the paper.

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## 2 PREVIOUS WORK

Histogram equalization (HE) based algorithms, adjusting gray-level distributions are commonly deployed in contrast enhancement as it is simple to use on biomedical images. It increases the dynamic range expansion by increasing each pixel's value, thereby enhancing the input image's contrast and brightness (Kim, 1997). This section summarizes the work on histogram equalization (HE) based algorithms previously proposed by various researchers.

Global histogram equalization stretches the image intensity level to the whole range of 8-bit values, 0 – 255, effectively increasing the dark-bright contrast of images (Mokhtar et al., 2009). Global HE is discriminative. It may introduce undesired intensity changes in a large block and may increase the noise level of images. Local HE was proposed to get rid of specific Global HE issues, but the method a) requires high computational cost, b) the output appearance depends on the size of selected local areas (Abdullah-Al-Wadud et al., 2007). Similarly, adaptive HE algorithms, taking advantage of global and local HE, were introduced to enhance broader applications (Singh et al., 2016).

Another research brightness preserving bi-histogram equalization (BBHE) is conducted by Kim (1997), which can preserve brightness and avoid false coloring. Moreover, dualistic sub-image histogram equalization (DSIHE) is similar to BBHE that input histogram is decomposed into two subsections (Patel et al., 2013). DSIHE performs better than BBHE regarding entropy and brightness preservation (Kalhor et al., 2019). Recursive mean separated histogram equalization (RMSHE) is an extended version of BBHE (Patel & Muthu, 2020). Compared to BBHE, RMSHE can preserve the original brightness of the image. Besides, dynamic histogram equalization (DHE) assists in the control of the effect of an image without losing important information in the image (Abdullah-Al-Wadud et al., 2007).

Besides, a method named contrast limited adaptive histogram equalization (CLAHE) is proposed by Reza (2004) used with Ostu to enhance biomedical image. A novel contrast enhancement algorithm Histogram equalization with adaptive gamma correction and homomorphic filtering (QWAGC-FIL) was developed by Monika Agarwal et al. (2017). This algorithm can enhance the image with low contrast while maintaining maximum entropy and enhancement control.

## 3 THE PROPOSED METHOD

The method proposed in this paper take advantages of global histogram equalization (GHE). As shown in Figure 2, an adaptive intensity mapping is applied before GHE to compensate issues of noise and unwanted colour boundaries, Figure 1.

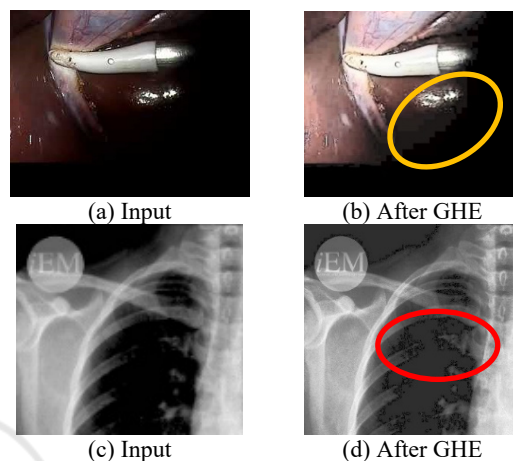


Figure 1: Issues of global histogram equalization, (a) and (b), unwanted colour boundaries in dark regions; (c) and (d), noise around edges are amplified after global histogram equalization.

The intensity mapping is done in the V channel of HSV colour space, where  $V = \max(R, G, B)$ . To calculate the mapping function, the input V channel should be divided into 3 sub-images, a noise part to determine the offset of the function, a relevant dark part to be mapped to a brighter value region and the bright part to determine how bright the dark part can be mapped to. To obtain the three parts, Ostu threshold is applied to the input channel, which output 2 sub-images where the inter-class variance of the histogram of the two sub-images are maximised.

After the initial thresholding:

- 1) If the dark part average is smaller than 32 ( $\text{thresh\_low}$ ) and the bright part average is greater than 64, the dark part will be used to measure the noise level; if the bright part average is smaller than 64, the image is an almost black image and is not currently considered in this paper.
- 2) If the dark part is recognised as the noise part, the bright part will be further divided into 2 sub-images using Ostu method. The averages and derivatives of the relevant dark and bright parts ( $\text{aved}$ ,  $\text{detd}$  and  $\text{aveb}$ ,  $\text{detb}$ ) and the maximum of the dark region,  $\text{maxd}$ , are recorded as respectively.

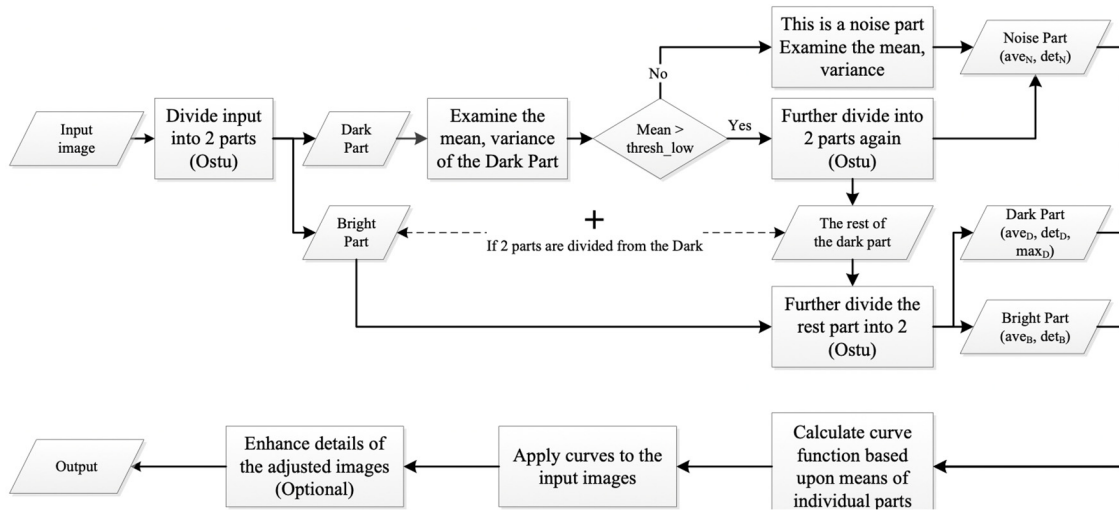


Figure 2: Workflow of the proposed algorithm.



Figure 3: Ostu thresholding.

- 3) If the initial divided dark part has averages larger than 32, this dark part is further divided until the noise part with mean value smaller than 32 is separated, the average of noise part is noted as  $ave_N$ .
- 4) After that, the rest of the image will be threshold (Ostu) into bright and dark parts. The average, variance, maximum,  $ave_D$ ,  $det_D$ ,  $max_D$  and  $ave_B$ ,  $det_B$  will be calculated accordingly.

Averages and derivatives of separated dark and bright parts are used to determine the shape of curve applying to the input images. Curves are designed following rules:

- a) After applying the curves, pixels in the dark parts should have smaller values than pixels in the bright parts;
- b) Logarithm curves  $g(x) = N_1 + N_1 \ln(x/N_1)$  is applied to pixels larger than  $N_1$  to improve the perceptive linearity of the relevant dark region
- c) Near saturation region is suppressed using sinuous function to reduce the area of near saturated region.

The result mapping function,  $f(x)$ , is:

$$f(x) = \begin{cases} (r_2 - 1)x + N_1 & x \text{ in } [0, N_1] \\ r_2 \left( N_1 + N_1 \ln \left( \frac{x}{N_1} \right) \right) & x \text{ in } (N_1, N_2] \\ r_3 x + b_3 - \left( A \sin \left( \frac{2\pi}{T} (x - N_2) \right) \right) & x \text{ in } (N_2, 255] \end{cases}$$

- 1) The curve starts from linear,  $x$  runs from 0 to  $N_1 = \max(ave_N - det_N, 0)$ , with the curve output in  $[N_1, r_2 N_1]$ , where  $r_2 = \frac{OutMaxV_2}{N_1 + N_1 \ln(\frac{N_2}{N_1})}$  is the ratio amplifying values in dark region from  $(N_1, N_2 = ave_D + det_D]$  to  $(r_2 N_1, OutMaxV_2]$ .
- 2) To avoid oversaturation at the same time maintain higher values in previous brighter part,  $OutMaxV_2$  is set to  $\min(N_1 + N_1 \ln(\frac{N_2}{N_1}), \max(ave_D * r + max_D * (1-r), 160))$  and  $r$  in  $[0, 1]$  is set to  $\frac{\min(det_D, det_B)}{\max(det_D, det_B)}$ .
- 3) The rest of the part connects the maximum output of the second ( $OutMaxV_2$ ) to the maximum of 8-bit output 255. Then,  $r_3 = \frac{255 - OutMaxV_2}{255 - N_2}$  and  $b_3 = 255(1 - r_3)$ . To suppress the near saturated
- 4) region, the half period of a sinuous function is subtracted, where  $T = 2(255 - N_2)$  is the period of the sinuous function,  $A$  is the magnitude of the sinuous function. In experiment,  $A$  is set to 20.
- 5) the sinuous function,  $A$  is the magnitude of the sinuous function. In experiment,  $A$  is set to 20.

When  $ave_N = 5$ ,  $ave_D + det_D = 130$  and the maximum value of dark region,  $OutMatV_2$ , is set to 130, the curve is demonstrated in Figure 4. Apply the mapping process to 8-bit colour will result in Figure 5(b), where the very dark and very bright pixels are mapped into the middle value range.

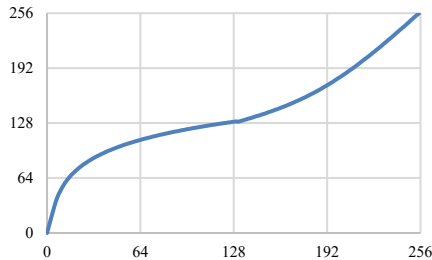


Figure 4: Curve with offset = 5, dark/bright division = 130.

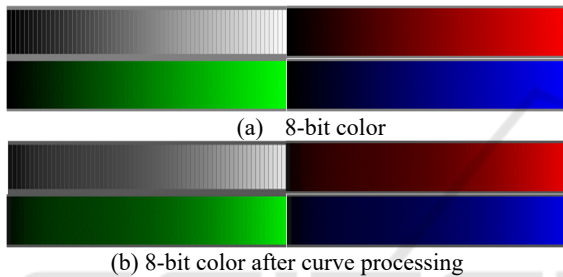


Figure 5: Curve and histogram equalization applied to 8-bit colours of gray (x, x, x), red (x, 0, 0), green (0, x, 0) and blue (0, 0, x) in order of (R, G, B), where  $x = [0, 255]$ .

The design of the intensity mapping function and the threshold selection is based on the non-linear perception of eyes in brightness and colour to the

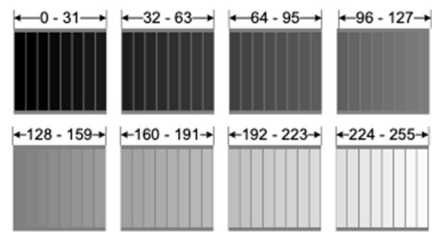


Figure 6: Grey scale 8-bit colour. From block (a) to block (h), intensity is gradually increased from 0 to 255. In each block, the intensity in each adjacent slice is increased by 4.

input pixel values. As the 8-bit gray scale colour bar demonstrated in Figure 6, the perception of intensity change varies in each group. Eyes are more sensitive to the colour difference in the mid-dark range (32 – 224) but not in the near black (0 – 32) and near saturated (224 – 255) range. Mapping the range of image intensities to the range of eye sensitive region will help eyes to perceive more details from the input. After intensity mapping, global histogram equalization will have wider range of input images with different intensity distributions. i.e. high contrast laparoscopic surgical frames will have peaks in dark and/or bright regions or X-ray images with pixels distributed in mid-range. As demonstrated in Figure 6, apply the algorithm to a high contrast laparoscopic image, the intensity of dark region will be increased to reveal more details and the amplification of brightness part is suppressed without saturation. Apply the same strategy to X-ray image, dark and bright pixels from the input will be more evenly distributed to obtain better eye perceived contrast.

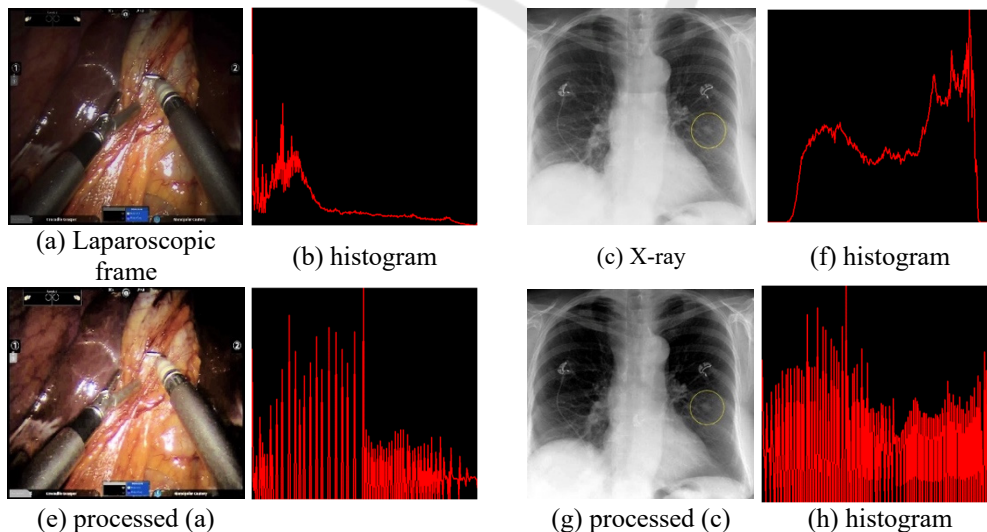


Figure 7: X-ray, laparoscopic surgical video frames (a, c) and their histogram (b, d) of intensity (V) calculated in HSV colour space.



## 4 EXPERIMENTAL RESULTS

To examine the algorithm, images from websites are tested. Following criteria are selected to evaluate the performance of the algorithm:

- Amount of details revealed before / after the application
- The colour consistency and truthfulness before and after the application
- Amount of noise, alien boundaries introduced through the application of the algorithm
- Perceived change in brightness

As demonstrated Figure 8, when applied to high contrast laparoscopic surgical frames, details including blood vessels and tissue patterns are better presented at the same time maintained the colour perception. Results of the algorithm applying to X-ray images are similar to results of GHE with less introduced noise level.

The algorithm is real-time capable for HD, 60fps, 1080\*1920 video frames with the processing speed

approx. 8ms per frame, profiled through 4-core, 2.8GHz CPU. For similar size X-ray images, the speed is around 3ms per image as only 1 channel is processed, and no colour space conversion is required.

## 5 CONCLUSIONS

This paper introduced a curve mapping and histogram equalization-based method to enhance perceived contrast and details of input biomedical images, colour or gray-scale. The method takes advantages of Ostu histogram analysis to adaptively separate images into sub-regions with similar intensity distributions, which intensively save the computational loads. Curve based mapping adopted from camera sensor processing map the image intensity to eye sensitive range to help global histogram equalization achieves better colour truthfulness and reduce noise in near black region.

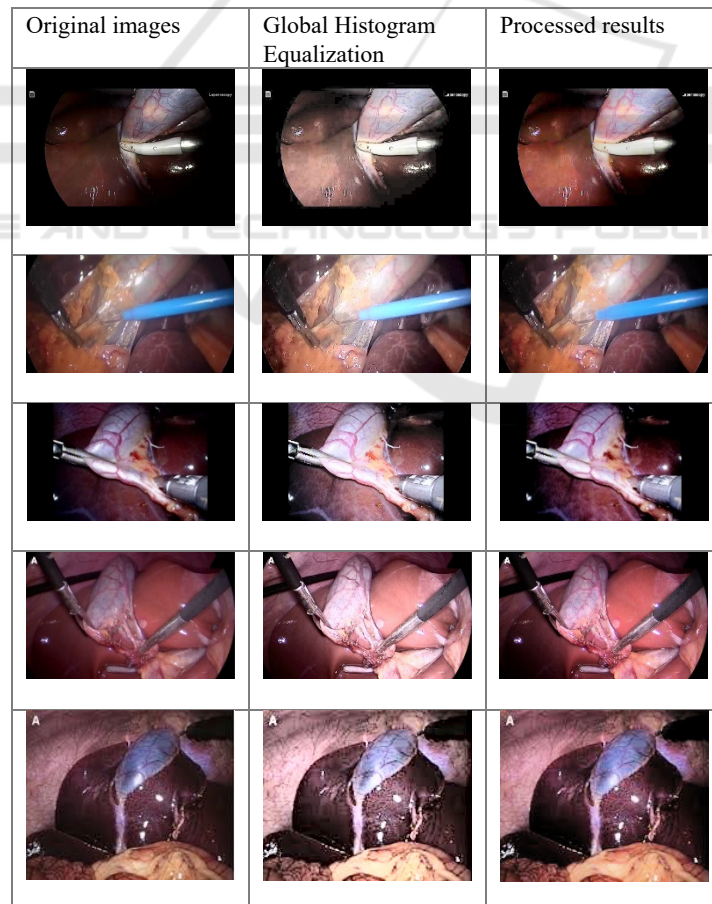


Figure 8: More results applied on website images.




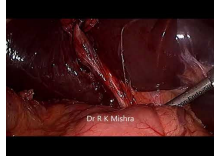

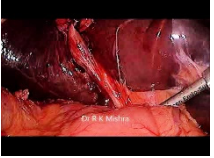



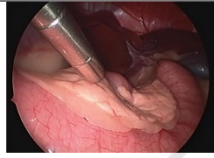
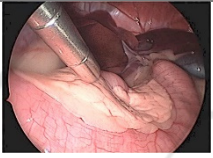
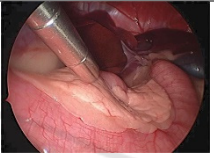

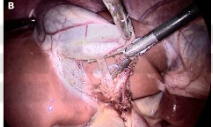


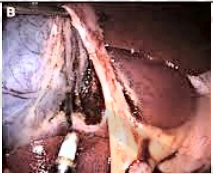
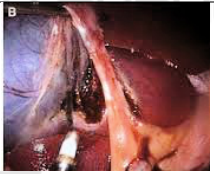

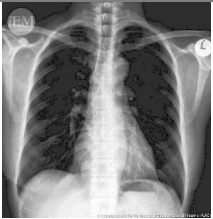
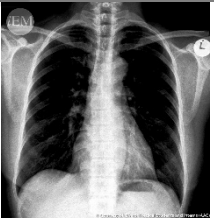
Original images	Global Histogram Equalization	Processed results
		
		
		
		
		
		
		

Figure 8: More results applied on website images (cont.).

## ACKNOWLEDGEMENTS

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## APPENDIX

Table 1: Source of images (in display order of Figure 8).

<a href="https://www.youtube.com/watch?v=fs_hJO1RZMs">https://www.youtube.com/watch?v=fs_hJO1RZMs</a> Lap chole basic, around 3:12	<a href="https://medtube.net/general-surgery/medical-videos/24250-laparoscopic-cholecystectomy-with-mishra-knot">https://medtube.net/general-surgery/medical-videos/24250-laparoscopic-cholecystectomy-with-mishra-knot</a>
<a href="https://www.youtube.com/watch?v=SpSNewRpdW0">https://www.youtube.com/watch?v=SpSNewRpdW0</a> Full length HD Laparoscopic Cholecystectomy with Critical View, around 3:44	<a href="https://www.youtube.com/watch?v=O4pO_RXELvE">https://www.youtube.com/watch?v=O4pO_RXELvE</a> Single incision robotic cholecystectomy, around 1:10
<a href="http://drkashi.science/?p=3211">http://drkashi.science/?p=3211</a> , Cefuroxime as a prophylactic antibiotic in laparoscopic cholecystectomy	<a href="https://smallanimal.vethospital.ufl.edu/clinical-services/internal-medicine/endoscopy/abdominal-endoscopy/">https://smallanimal.vethospital.ufl.edu/clinical-services/internal-medicine/endoscopy/abdominal-endoscopy/</a> , Abdominal Endoscopy
World J Gastrointest Surg. Feb 27, 2019; 11(2): 62-84, Figure 13	
Voermans, Rogier P., et al. "Hybrid NOTES transgastric cholecystectomy with reliable gastric closure: an animal survival study." Surgical endoscopy 25.3 (2011): 728-736. Figure 1	
<a href="https://www.flickr.com/photos/iem-student/29110322657">https://www.flickr.com/photos/iem-student/29110322657</a>	<a href="https://www.waybuilder.net/swecthaven/MedTech/Dental/DentalRad/default.asp?iNum=0303">https://www.waybuilder.net/swecthaven/MedTech/Dental/DentalRad/default.asp?iNum=0303</a>