

Bounded Iterative Thresholding for Lumen Region Detection in Endoscopic Images

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Abstract—The development of a fully automated robotic endoscopic steering system has been an active area of research for more than a decade. This paper aims at proposing a hardware-efficient iterative thresholding strategy to locate the lumen region in captured endoscopic images in order to enhance traditional endoscopes with certain degree of autonomy and intelligence. The proposed method is characterized by a definite requirement on the number of iterations of thresholding in order to detect the lumen region. The proposed algorithm has been demonstrated to be robust against varying characteristics using real endoscopic sample images. The reduction in the number of operations required by the proposed method can be up to 71% compared to a previously reported method. FPGA synthesis results of the proposed approach confirm its viability for real-time realization.

Keywords—computer vision; FPGA; hardware acceleration; medical images

I. INTRODUCTION

Medical endoscopy is a minimally invasive procedure to investigate various internal cavities in the human body (e.g. lower gastrointestinal tract and respiratory tract) for diagnosis and therapy. Micro-robotic endoscopes with support for computer-aided automated navigation have emerged to alleviate the pain and discomfort risks in endoscopy. As illumination in endoscopes is provided by a point light source, the region characterizing the farthest piece of tissue appears to be the darkest in the captured endoscopic image and is referred to as the lumen region. The identification of the lumen region and navigation of the endoscope towards the lumen center is the principal technique used for automated robotic endoscopic steering system. Since the advent of endoscopes with digital imaging chips, several endoscopic image processing techniques have been proposed for the identification of the lumen contour and lumen center in order to provide decision support for diagnosis and to provide support for navigation. Extraction of the precise lumen contour is essential when it comes to diagnosis. The contour, however, might not be conspicuous in every image and it is an optional requirement for navigation [1]. Moreover, extraction of the precise contour could be too slow for meeting real time requirements. Thus, for the purpose of automating endoscope navigation, the robust identification of the center of the lumen is sufficient to precisely control the endoscope orientation [2]-[6].

Several hardware-based image processing algorithms on segmentation and region growing have been proposed as software approaches optimized for microprocessors may not be fast enough for real time processing. FPGAs come across as a viable choice for the implementation of real time image processing algorithms allowing for a dedicated hardware solution that exploits parallel and pipelined design techniques. The challenges in designing robust image processing algorithms stem from imaging conditions in the gastrointestinal tract that tend to be challenging as the background illumination and reflective properties may not be uniform throughout. Also, the shape, size and pixel intensities of the lumen region in captured images might vary significantly.

This paper aims at proposing a hardware-efficient iterative thresholding strategy to locate the lumen region in captured endoscopic images. The detection of the lumen region serves as a pre-requisite step for the identification of the lumen center. The proposed bounded iterative thresholding algorithm is characterized by a definite requirement on the number of iterations of thresholding in order to detect the lumen region. Simulations were carried out in Matlab, for a class of 40 gray-level endoscopic images of size 256x256, to demonstrate the robustness of the proposed method for lumen region detection. When compared to a previously reported approach, the proposed method leads to significant reduction in computational complexity. In addition, FPGA synthesis results show that the proposed approach lends itself well for real-time realization.

In the next section, we review existing works in the literature for the extraction of lumen region. In Section 3, we highlight limitations of an existing work for detecting the lumen region, and Section 4 describes the proposed bounded iterative thresholding algorithm for lumen region detection. This is followed by a discussion on experimental and FPGA synthesis results in Section 5. Section 6 concludes the paper.

II. RELATED WORK

The work in [7] presented a technique for automatic extraction of lumen region and its boundary by using a combination of a progressive thresholding technique and region growing. A quasi Region of Interest (RoI) is obtained after two iterations of Otsu's thresholding [8]. In order to facilitate automatic segmentation, an adaptive progressive thresholding (APT) approach was suggested in [9]. A Cumulative Limiting

Factor (CLF) is used to identify the optimal threshold in every iteration. The APT method was combined with a Differential Region Growing (DRG) approach in [10] for the extraction of the lumen region based on the similarity of pixels.

An efficient pipelined architecture for the implementation of APT on FPGA has been proposed in [9]. The architecture was further improved by replacing the complex multiplication and division operations involved in Otsu analysis with an efficient logarithm conversion unit [11]. However, the APT method results in more than 100 sequential iterations for certain endoscopic images which may not be appropriate for real time implementation.

Wang et. al [5] suggested a technique for lumen center detection which involves adaptive thresholding followed by erosion and dilation. Factors that represent the upper and lower limits of the ratio of dark region to the area of the whole endoscopic image need to be predetermined by experimenting with a good set of images. The adaptive threshold value needs to be determined based on the comparison of the whole area of the image against these predetermined factors.

Tian et. al. [12][13] suggested the use of an Iris filter in order to obtain a very accurate boundary of the lumen in endoscopic images. A preliminary RoI is extracted through APT and the remaining areas of the image which are beyond the threshold value are eliminated and considered as background. Having such a uniform background is a precondition to be met for the use of Iris filter. The lumen boundary obtained on applying the Iris filter involved large number of trigonometric computations in the convergence index calculations. Though efficient CORDIC architectures have been suggested in [13] for the hardware implementation of the trigonometric computations, such a complex technique to obtain the accurate lumen boundary is not essential for the case of endoscopic navigation.

A distinct algorithm using fuzzy region growing was suggested by Chang et. al. to segment the lumen region from endoscopic images [14]. The fuzzy rule method has been implemented on FPGA with a pipelined architecture. The fuzzy region growing is preceded by thresholding the image with an optimal threshold obtained at the end of an iteration of Otsu's technique. In spite of being a feasible implementation, this method is limited in accuracy as only a single iteration of Otsu is employed.

Lim et. al. [4] proposed a technique for locating the center of mass (CoM) of the lumen in endoscopic images using a novel APT approach to identify the lumen region that is followed by a windowing operation to determine the lumen center. The APT is terminated when the maximum Between Class Variance (BCV) identified by the Otsu method in an iteration is less than the maximum BCV of the previous iteration.

III. LIMITATION OF EXISTING APT METHOD

The Otsu's technique segments the histogram of the endoscopic image into two distinct classes. Let C_1 and C_2 represent the two classes to be obtained after a segmentation by threshold t , with P_1 and P_2 referring to the probability function

of a pixel belonging to class C_1 and C_2 respectively. The probability functions are calculated as shown below.

$$P_1 = \omega_t = \sum_{i=0}^t \frac{n_i}{N} \quad (1)$$

$$P_2 = \omega_0 = 1 - \omega_t \quad (2)$$

Let n_i be the number of pixels which have an intensity value of i and N the total number of pixels in the image, and L the number of gray levels.

$$\mu_T = \sum_{i=0}^{L-1} \frac{i \times n_i}{N} \quad (3)$$

$$\mu_t = \sum_{i=0}^t \frac{i \times n_i}{N} \quad (4)$$

The Otsu method suggests that the optimal threshold can be obtained through the sequential search for the maximum of between class variance (BCV) $\sigma_B^2(t)$, for the values of t where $0 \leq t < L$:

$$\sigma_B^2(t) = w_0(1 - w_0) \left(\frac{\mu_T - \mu_t}{1 - w_0} - \frac{\mu_t}{w_0} \right)^2 \quad (5)$$

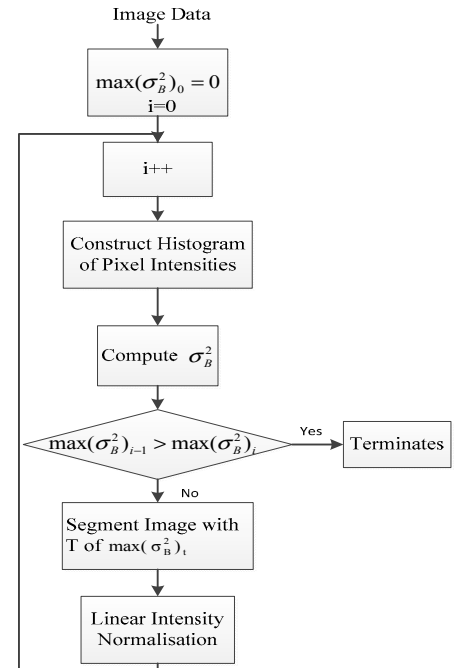


Fig. 1: APT method in [4]

The APT method proposed in [4] involves discriminant analysis by Otsu method and intensity normalization for every iteration until a termination condition is met (see Fig. 1). In particular, the APT is terminated when the maximum BCV identified by the Otsu method in the current iteration is less than the maximum BCV of the previous iteration. Our experiments reveal that for certain images, the APT algorithm

proposed in [4] does not terminate at the right point. While for some images the final thresholded image obtained after termination of the algorithm does not have a well segmented lumen region, for certain other images the final thresholded image has all the pixels merged into the background. In order to validate the effectiveness of the APT method, we perform the windowing operation in [4] on the final segmented lumen region to locate the lumen center.

For the endoscopic image shown in Fig. 2(a), the APT method in [4] terminates after 2 iterations. However, it can be observed from the final thresholded image in Fig. 2(b) that significant background remains in the image. Determining the lumen center on this segmented image gives incorrect results as there is significant influence from the background that is left behind and the problem is further complicated as the lumen region is small. It can be observed that the final lumen center identified, highlighted in red in Fig. 2(c), is well outside the lumen region. On the other hand, for the endoscopic image shown in Fig. 3(a), APT terminates after 6 iterations, though 2 iterations of Otsu based thresholding would actually suffice for this case. Fig. 3(b) shows the final thresholded image obtained for the endoscopic image in Fig. 3(a) after 6 iterations, with all the pixels having been merged into the background. Fig. 3(c) shows the thresholded image after 2 iterations, which would have been sufficient for accurate detection of the lumen region.

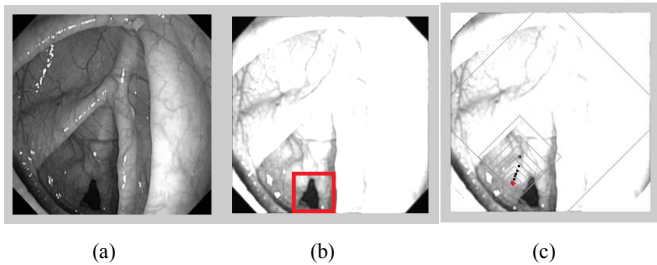


Fig. 2(a): Original endoscopic image; (b) final thresholded image of (a); (c) windowing operation to determine lumen center

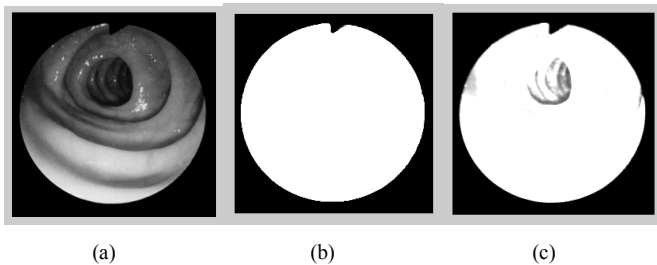


Fig. 3(a): Original endoscopic image; (b) over thresholded image of (a) after 6 iterations; (c) thresholded image after 2 iterations

Hence there is a need to refine the APT method in [4], as it results in under-thresholding (Fig. 2(b)) or over-thresholding (Fig. 3(b)) for some images. Moreover, automatic termination according to the maximum condition does not happen for all cases. Out of 40 sample endoscopic images that were tested, the APT method in [4] was unable to provide a well segmented image for 10 of them.

IV. PROPOSED METHOD

The proposed APT approach stems from observation that a maximum of 3 iterations were sufficient in order to obtain a thresholded image with a well segmented lumen region. In addition, the decision to perform the third iteration depends on the number of pixels between the two histogram peaks obtained in an iteration of the Otsu method.

Fig. 4 illustrates the over-thresholding problem in [4]. The histograms of the original image and the thresholded image after the 1st, 2nd and 3rd iterations of thresholding are shown in Fig. 4 for the endoscopic image in Fig. 4(a). The APT algorithm in [4] terminates automatically after 3 iterations and results in over-thresholding as shown in Fig. 4(f). It can be observed that the histogram of the thresholded image obtained after 2 iterations in Fig. 4(d), has 2 discernible peaks, *Peak1* and *Peak2*. *Peak1* refers to the maximum pixel count for the intensity in the low intensity region which would constitute the lumen region, while *Peak2* refers to the number of background pixels. The difference in pixel count Δ between *Peak1* and *Peak2* after 2 iterations of thresholding is highlighted in Fig. 4(d). Though the APT method in [4] terminates only after 3 iterations, 2 iterations of thresholding would suffice to obtain a final thresholded image with a well segmented lumen, as it can be seen from Fig. 4(d) that Δ is a large enough to discern between the two peaks.

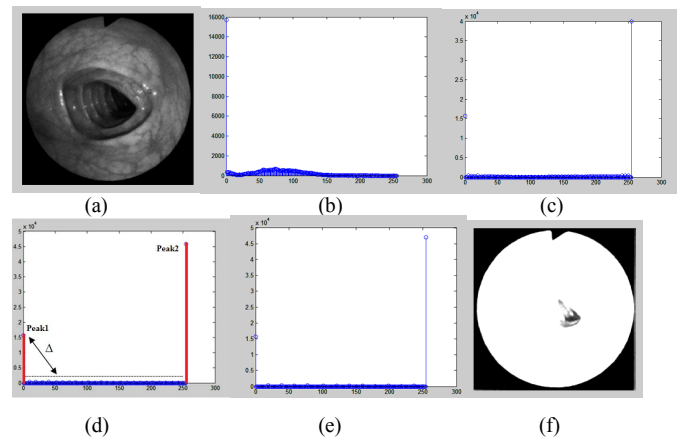


Fig. 4(a): Original endoscopic image; (b) original histogram; (c) histogram after 1st iteration; (d) histogram after 2nd iteration; (e) histogram after 3rd iteration, (f) over-thresholded image after 3 iterations using the method in [4]

Fig. 5 illustrates the under-thresholding problem with the method in [4]. For the endoscopic image in Fig. 5(a), the APT method in [4] terminates automatically after the 2nd iteration. This results in an under-thresholded image as shown in Fig. 5(e). When compared to Fig. 4(d), it can be observed that the histogram after the 2nd iteration in Fig. 5(d) has very low *Peak1* and the gray level intensities between the *Peak1* and *Peak2* have a contribution comparable to that of *Peak1*. This makes it necessary to have a 3rd round of thresholding in order to obtain a final thresholded image with a well segmented lumen.

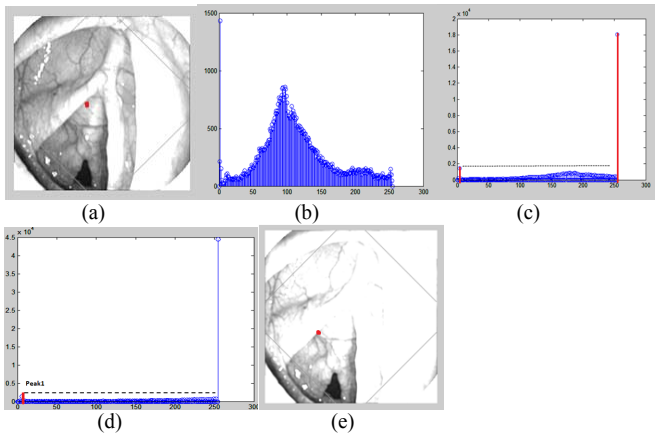


Fig. 5(a): Original endoscopic image; (b) original histogram; (c) histogram after 1st iteration; (d) histogram after 2nd iteration; (e) under-thresholded image after 2 iterations using the method in [4]

The analysis of the histograms in Fig. 4 and Fig. 5 demonstrates that in order to have the lumen as a predominant object, the thresholding iterations should continue until $Peak1$ is significantly higher than the contribution from other intermediate pixel intensities (pixels between $Peak1$ and $Peak2$). In addition, it was observed that even in the case where $Peak1$ has over 2000 pixels after the 2nd iteration, a 3rd iteration of thresholding was necessary for the images which had a comparable contribution from intermediate intensities between $Peak1$ and $Peak2$. Specifically, it was observed that when 3 intermediate intensities have a significant pixel count of over 500 pixels, it is necessary to further threshold the image to ensure that the final thresholded image has the lumen as the predominant object.

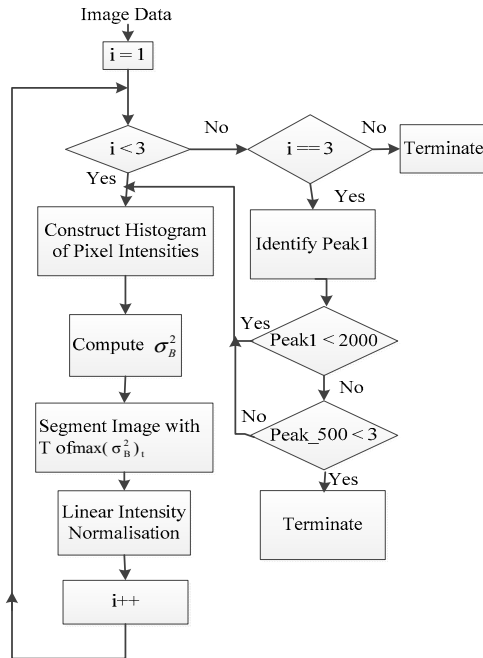


Fig. 6: Proposed bounded iterative thresholding algorithm

Let's denote $Peak_500$ as the number of bins between the 2 peaks, whose pixel count exceeds a value of 500. Fig. 6 illustrates the proposed bounded iterative thresholding

algorithm. It can be observed that the Otsu thresholding is performed twice for each image, and a third iteration is only undertaken if $Peak1$ is less than 2000 after the second iteration, or if $Peak_500$ is less than 3 after the second iteration.

The values used for the comparisons of $Peak1$ and $Peak_500$ were obtained from experiments based on the 256x256 endoscopic images. It is noteworthy that the proposed technique can also be extended to images of a different resolution using the following methodology. The number of iterations of thresholding, say n , can be determined based on a reasonable number of training images. The histograms obtained after n iterations of thresholding for all the training images can be analyzed to obtain a reliable estimate for the minimum value of $Peak1$. If $Peak1$ of the histogram obtained after n iterations happens to be less than the minimum value for certain images, another final iteration of thresholding is needed in order to better distinguish the small lumen by reducing the contribution of background pixels. Also, for the endoscopic images where $Peak1$ of the histogram obtained after n iterations of thresholding exceeds the minimum value, another final iteration of thresholding is necessary only if the contribution of background pixels is still comparable to the value of $Peak1$. For instance, if there are a significant number of bins in the histogram obtained after n iterations of thresholding, whose pixel counts add up to a value comparable to $Peak1$, then another final iteration of thresholding can help to obtain a thresholded image with the lumen as the predominant object. Hence the determination of the value of n and $Peak1$ are the key steps in extending the proposed technique for a new set of images with different resolutions.

V. EXPERIMENTAL RESULTS

In this section, we compare the proposed bounded iterative thresholding algorithm with the baseline algorithm in [4], in terms of the quality of the detected lumen regions, and computational complexity. We will also discuss synthesis results to demonstrate the viability of the proposed method for real-time implementation. The experiments were performed on 40 gray-level endoscopic images of size 256x256

A. Effectiveness of lumen region detection

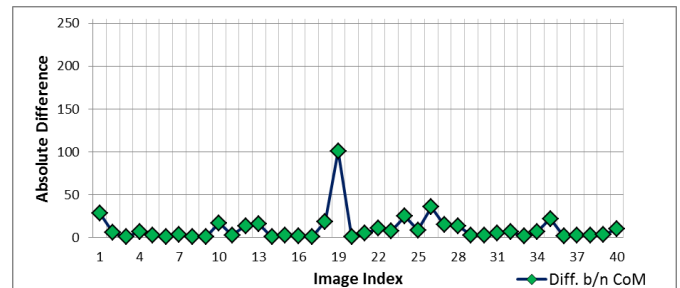


Fig. 7: Comparison of lumen centers identified by the proposed and baseline algorithms

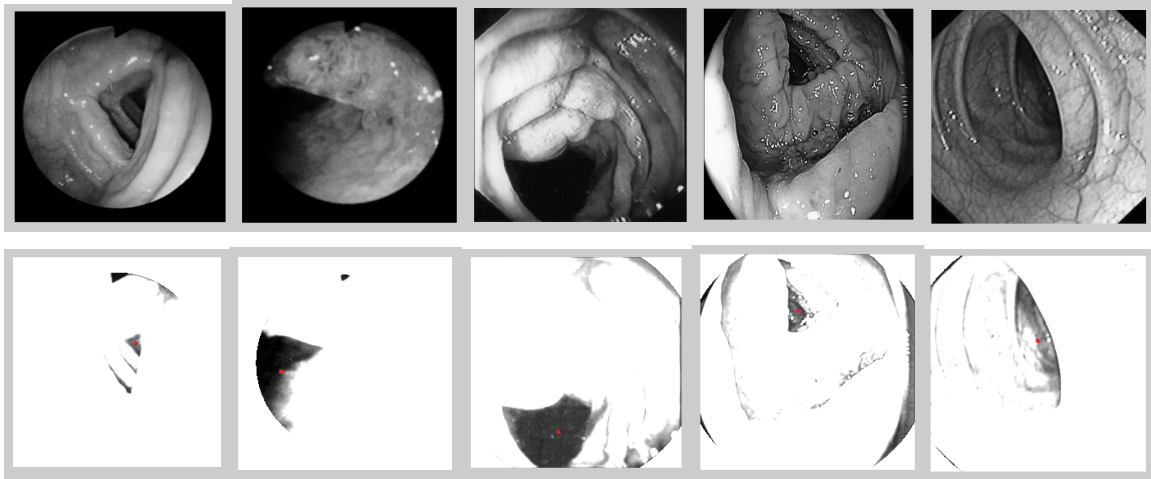


Fig. 8: Endoscopic images (top) and the thresholded images (bottom) using the proposed technique, which enables accurate lumen centers to be detected

In order to compare the quality of the detected lumen regions between the baseline algorithm and the proposed method, we perform the windowing operation in [4] to locate the lumen centers of the detected lumen regions for both techniques. Fig. 7 shows the absolute difference between the lumen centers identified by the proposed method and the baseline method. It can be observed that the results of both the algorithms are in very close conformance except for image 19. For this endoscopic image, the windowing algorithm is unable to identify the lumen center correctly for the baseline algorithm as the lumen region is small. However, the proposed method leads to the identification of the correct lumen center. Fig. 8 shows the lumen center identified by the proposed method for some of the endoscopic images used in the experiments. It can be observed that the proposed technique correctly identifies the lumen center for all the cases.

B. Computational Complexity Analysis

The steps and maximum number of operations required for a single iteration of Otsu is shown in Table 1.

TABLE I

I. Histogram and Intensity Area (IA) Computation		
1.	Determine $n_i \forall i \in [0,255]$ by scanning all pixels	65536 additions
2.	$i*n_i, \forall i \in [0,255]$	256 Multiplications
II. Cumulative Histogram and Cumulative IA Computation		
3.	$\sum_{i=0}^t n_i \forall t \in [0,255]$	255 Additions
4.	$\sum_{i=0}^t i*n_i \forall t \in [0,255]$	255 Additions
III. Maximum BCV Computation		
5.	$\mu t \forall t \in [0,255]$	256 Divisions
6.	$\omega t \forall t \in [0,255]$	256 Divisions
7.	$\sigma_B^2(t) \forall t \in [0,255]$	2 Multiplications and 2 Division for every t \Rightarrow 512 Multiplications and 512 Divisions

It can be observed that the computational complexity for a single iteration of thresholding for both the baseline and proposed method is notably high, and hence reducing number of iterations for lumen region detection can significantly lower the computational complexity. The number of Otsu iterations incurred by the proposed and baseline method for the sample endoscopic images are presented in Fig. 9.

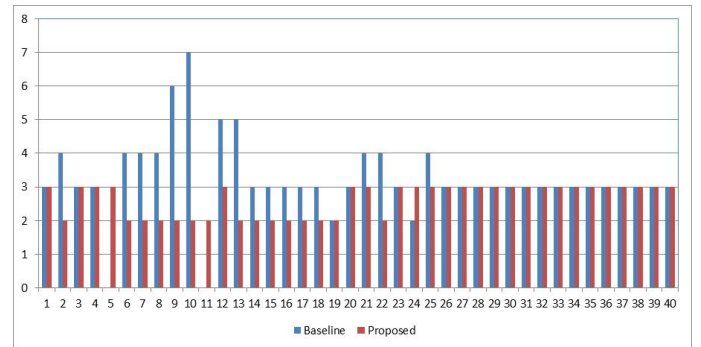


Fig. 9: Number of Otsu iterations required by the baseline and proposed method for 40 endoscopic images

The number of Otsu iterations performed by the baseline algorithm ranges between 2 and 7 (zero iterations for the baseline indicates that it is unable to terminate). On the contrary, the proposed algorithm performs 2 to 3 iterations of Otsu based thresholding. The need for a 3rd iteration is determined based on the intensity histogram of the image obtained after 2 iterations as explained in the previous section. The proposed algorithm requires lesser or the same number of iterations compared to the baseline algorithm for all the images considered except for image 24, where the proposed method requires one iteration more than the baseline. In addition, there are two cases (image 5 and 11), where the baseline algorithm is unable to terminate, but the proposed algorithm is able converge in 2-3 iterations. Hence the proposed algorithm leads to lower number of Otsu iterations, which in turn results in significant reduction in the computational complexity. On average, the proposed algorithm requires 20% lesser number of multiplications and

divisions when compared to the baseline method. The reduction in the number of multiplications and divisions can be as much as 71% (for image 10).

C. FPGA implementation results

The main computational blocks of the proposed bounded iterative thresholding technique consist of 3 stages. The first stage comprises of the module for computing the intensity histogram. A dual port BRAM with 256 locations, each of width 16-bit is used to store the intensity histogram.

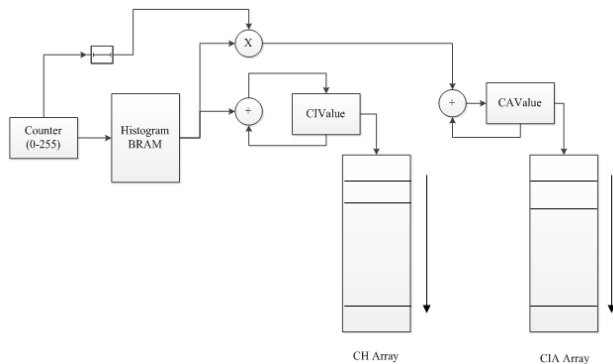


Fig. 10: Architecture for computing CH and CIA

When all the 65536 pixels of the endoscopic image have been accounted for in the histogram, a signal indicating the end of this task initiates the subsequent stage which involves the computation of the Cumulative Histogram (CH) and Cumulative Intensity Area (CIA). Fig. 10 shows the architecture for generating the CH and CIA. Two arrays consisting of 256 registers each were used for obtaining the CH and CIA. The contents of the Histogram BRAM are read successively and accumulated in a temporary register CIValue. In parallel, intensity area data are accumulated in another temporary register CAValue (third stage). Thus, as the contents of the Histogram array are read, the updated values of CIValue and CAValue are pushed into the register arrays of CH and CIA respectively. The architecture for computing the maximum BCV is not shown.

The proposed design was synthesized for the Xilinx Spartan 6 (XC6SLX45-CSG324) device and the synthesis results are shown in Table 2. From the simulation results it can be estimated that it takes approximately 65800 clock cycles to generate CH and CIA for a 256x256 endoscopic image in a single iteration of the proposed method. Since the proposed method is bounded by a maximum number of 3 iterations, it only requires at most 2.3ms to detect the lumen region of a single endoscopic image.

TABLE 2

AREA		MAXIMUM FREQUENCY
Number of SLICE LUTS	Number of SLICE registers	
123	56	85.75MHz

VI. CONCLUSION

In this paper, we proposed a bounded iterative thresholding algorithm for detecting the lumen region of endoscopic images that limits the number of Otsu iterations to 3. A 3rd iteration of thresholding is performed only if deemed necessary by analyzing the histogram peak corresponding to the lumen region and the intermediate pixel counts between the two discerning peaks after the second iteration. Simulations on an extensive set of 40 endoscopic images of size 256x256 show that the proposed method is more robust and lead to significant reduction in the computational complexity when compared to the baseline algorithm. The FPGA synthesis results of the proposed method further justifies its real-time capability.

REFERENCES

- [1] V. K. Asari, S. Kumar, I. M. Kassim, "A Fully Autonomous Microrobotic Endoscopy System", *Journal of Intelligent and Robotic Systems*, 28: 325–341, 2000.
- [2] M. Liedlgruber, A. Uhl, "A Summary of Research Targeted at Computer-Aided Decision Support in Endoscopy of the Gastrointestinal Tract", Technical Report 2011-01, Universitat Salzburg, April 2011.
- [3] M. Liedlgruber, A. Uhl, "Endoscopic Image Processing - An Overview", *Proceedings of the 6th International Symposium on Image and Signal Processing and Analysis*, December 2009, pp. 707-712.
- [4] C.S. Lim, H. Tian, G. Sadana, T. Srikanthan, "High Speed Technique for Automatic Guidance of Microrobotics in Endoscopic procedures", *Proc. of the 4th Annual IEEE EMBS Conference on Information Technology Applications in Biomedicine (ITAB)*, Birmingham, UK, April 2003, pp. 130-134.
- [5] P. Wang, S. Krishnan, Y. Huang, N. Srinivasan, "An Adaptive Segmentation Technique for Clinical Endoscopic Image Processing", *Proceedings of the Second Joint Conference and the Annual Fall Meeting of the Biomedical Engineering Society EMBS/BMES Conference*, Vol. 2, 2002, pp.1084-1085.
- [6] R. Reilink, S. Stramigioli, and S. Misra, "Image based Flexible Endoscope Steering", *IEEE/RSJ International Conference on Intelligent Robots and Systems*, October 2010, pp. 2076-2082
- [7] S. Kumar, K. Asari, D. Radhakrishnan, "Real-time Automatic Extraction of Lumen Region and Boundary from Endoscopic Images", *Journal Med & Bio. Eng. & Comput.*, Vol.37, No.5, September 1999, pp. 600-604
- [8] N. Otsu, "A Threshold Selection Method from Gray-Level Histograms", *IEEE Transactions on Systems, Man and Cybernetics*, vol. 9(1), 1979, pp. 62-66
- [9] K. Asari, T. Srikanthan, S. Kumar, D. Radhakrishnan, "A Pipelined Architecture for Image Segmentation by Adaptive Progressive Thresholding", *Microprocessors and Microsystems*, 23(8-9), December 1999, pp. 493-499.
- [10] K. V. Asari, "A Fast and Accurate Segmentation Technique for the Extraction of Gastrointestinal Lumen from Endoscopic Images", *Medical Engineering & Physics* 22, Elsevier, 2000, pp. 89–96
- [11] H. Tian, S. K. Lam and T. Srikanthan, "Area Time Efficient Between-Class Variance Module for Adaptive Segmentation Process", *IEE Proc.-Vis. Image Signal Process*, Vol. 150, No. 4, August 2003, pp. 263-269
- [12] C. S. Lim, H. Tian, T. Srikanthan, "An Automated Technique for High Speed Segmentation of Endoscopic Images", *Proceedings of 2004 International Symposium on Intelligent Multimedia, Video and Speech Processing*, Hong Kong, October 2004
- [13] C. S. Lim, S. K. Lam, H. Tian and T. Srikanthan, "Efficient Architectures for Segmentation of Endoscopic Images in Micro-Robotic Auto Navigation Systems", *International Journal of Humanoid Robotics*, Vol. 3, No. 4, World Scientific, 2006, pp. 523–545
- [14] C. H. Chang, H. Tian, T. Srikanthan and C. S. Lim, "Field Programmable Gate Array based Architecture for Real Time Image Segmentation by Region Growing Algorithm", *Journal of Electronic Imaging* 11(4), SPIE, October 2002, pp. 469–478