Specular Reflection Detection for Early Prediction of Cervix Cancer

Pratik Oak and Brijesh Iyer

Abstract The specular reflection (SR) occurs in an image due to reflection from surface and affects the overall interpretation of the image. In medical image analysis, SR images reduce the diagnostic accuracy. Hence, the paper reports the analysis of various SR detection techniques and suggests the best one for automatic detection of SR pixels. The present work compares three state-of-art methodologies of SR detection and three automatic threshold selection techniques. We suggest the combination of '*Alsaleh*' method adapted by '*Kittler*' auto-selection technique for accurate SR detection. The SR free Cervix image will lead to the early detection of Cervix cancer.

Keywords Cervix cancer · Specular reflections (SR) · Threshold · Kittler technique

1 Introduction

Cervical cancer is the fourth most frequent cancer in women across the world. According to WHO health report, every fifth women in the world will be affected by it by 2050. Approximately 90% the 270,000 deaths from cervical cancer in 2015 occurred in low-and middle-income countries. The high mortality rate from cervical cancer could be reduced through a comprehensive approach that includes prevention, early diagnosis and effective screening and treatment programmes [1]. Cervix cancer can be cured if detected at its early stage. Hence, it becomes very important to analyze and detect this cancer at early stage. Conventionally, the Pap smear test is widely used to detect cervix cancer. However, this method suffers from its inherent disadvantages like high dependence on the operators' skills, requirement of subjects' attentions and cooperation and very painful too for the subject.

P. Oak · B. Iyer (✉)
Department of E & TC Engineering, Dr. Babasaheb Ambedkar Technological University, Lonere, Raigad, Maharashtra, India
e-mail: brijeshiyer@dbatu.ac.in

P. Oak
e-mail: pratik24hours@gmail.com

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The advancement in the field of medical image processing paved a new line of treatment for this decease. Cervix image analysis plays an important role as a complementary method to the existing methods in the confirmation of the disease. The idea is to capture the image of cervix during woman's routine health checkup and its processing to detect and predict the existence of cancerous tissues. There are various types of cervical images used in medical analysis like colposcopy, cytology, cervigrams, histology etc.

Noise is the most vulnerable issue as far as images are concerned. Removal of noise from the captured images is a prevalent challenge for the medical image processing. Specular Reflection (SR) is a bright spot on an image which contains maximum part as a white intensity which can be induced in cervix images and disturbs the process of extracting the information.

Few notable contributions are reported by various researchers in the area of detection of SR pixels from an input image. Dichromatic reflection model was used to represent SR pixels as separate regions [2]. Separation of RGB planes of a color image and logical *ANDing* of white pixels of each plane as a SR region was suggested by Das et al. [3]. This approach suffers from the trade-off of implementation ease and inferior accuracy on account of non-detection of less bright SR pixels. Akbar and Herman [4] proposed a segmentation using chaotic clonal selection algorithm. The proposed segmentation method lacks in images having smooth color illumination in texture. Based on the reported literature, SR detection methods can be broadly divided into three main categories such as use of kernel as a filter, SR as a binary classification problem and use of thresholding technique [5–7]. These techniques suffer from one or other drawbacks such as requirement of arbitrary constants during automatic detection of SR pixels and requirement of the training system every time for SR detection. The summary of state of the art SR detection techniques is given in Table 1.

However, the detection system should be fully automatic and independent of database. The present work reports the use of automatic threshold selection technique for SR detection. The paper is organized as: Sect. 2 reports the methodology adopted in the analysis whereas the results and discussion are included in Sect. 3. The paper is concluded in Sect. 4 along with the future scope of the work.

2 The Detection Methodology

Three state-of-art techniques of automatic thresholding are selected based on their simplicity and popularity in the reported literature. Existing methodologies for SR detection employed the arbitrary constants as the threshold. Automatic thresholding technique is used in SR detection which will replace the arbitrary constant proposed in the reported methods.

Table 1 State of the art SR detection techniques

Contribution	Methodology	Remark
Suo et al. [2]	Dichromatic reflection	Cannot differentiate pixels having same hue and different saturations
Das et al. [3]	Separation of RGB planes of a color image and logical ANDing of white pixels	Suffers from the trade-off easy to implement and inferior accuracy on account of non-detection of less bright SR pixels.
Akbar and Herman [4]	Segmentation using chaotic clonal selection algorithm	Inaccurate for images having texture color similar to illumination color
Zimmerman et al. [5]	Thresholding in HSI color plane and gradient image	Detection of non-SR pixels due to gradient image calculation
Xue et al. [6]	Morphological top hat transform	Affects the SR detection with variation in shape of structuring element
Alsaleh et al. [7]	Thresholding in HSI color plane	Database dependent method due to arbitrary selection of constant

2.1 SR Detection

Three state-of-art methods of SR detection are chosen based on their popularity in the reported literature. For the present analysis, ‘Intensity-Saturation (IS)’ histogram is the principle consideration for occurrence of SR region. SR pixels exist in dark region of saturation image (S) and bright region of intensity image (I) [8]. Hence, it is preferred to convert input color image from RGB to HSI plane.

HSI plane based cervix image analysis was reported by Zimmerman et al. [5]. They suggested a multiplying factor of 0.4 and 0.6 to be multiplied with maximum intensity of I and S respectively. The pixels appearing greater than this multiplication factor of I image and less than that of **S** image are separated. The magnitude of the gradient image of these separated pixels is considered as SR pixels.

Xue et al. [6] predefined the structuring element (SE) as a kernel and applied morphological top-hat transform on I image of input cervigrams. The Otsu method is applied on gray version of this transformed image to get SR pixels in the output.

Alsaleh et al. [7] proposed another combination of multiplying factors on the lines of work reported by Zimmerman et al. [5]. The authors suggested three combinations of multiplication factors i.e. 0.5 & 0.17, 0.7 & 0.07 and 0.8 & 0.19 for various types of database.

2.2 Automatic Threshold Detection Techniques

The arbitrary constants reported by most of the methods may vary with the database under experimentation. An automatic threshold selection may resolve this limitation.

Various threshold selection techniques are reported in the literature which can be used according to input image attributes. These techniques can be broadly classified as histogram based, clustering based, entropy based, object attribute based and statistical relation based approaches. The selection of a particular approach depends on the necessity of single or multiple thresholds and foreground and background region detection. The present work aims to select a single constant as the threshold and apply over the image. Hence, histogram based automatic threshold selection technique has been selected for this work. Three techniques based on their significance recorded in the literature, namely *Otsu*, *Riddler* and *Kittler* are selected for the present analysis [9].

Otsu technique reduces the intra-class variance between left and right-side histograms. Its optimal performance is obtained for images having a clear valley between two modes of histogram. It is commonly used automatic threshold selection method for grey as well as binary images [10]. *Calvard and Riddler* suggested opting the mean of input histogram as a threshold. It iteratively updates the threshold as average of lower mean and upper mean of histogram and stops at zero threshold difference [11].

Kittler method depends on principle of minimum error thresholding based on standard deviation of two histograms. This method is good for images having proper foreground. For all values of thresholds over the range of histogram, it computes the error between entropy and information with respect to deviation. It calculates the criterion function and considers its minimum value as a final threshold [12]. These three automatic threshold selection techniques are applied on three SR detection methods explained in 2.1 for the analysis of SR pixel detection.

Figure 1 depicts the flowchart for the proposed experimentation work. Stage I in Fig. 1 indicates the threshold values (T1 and T2) reported in state-of-art methods. Stage II lists automatic threshold selection techniques used in the present work.

3 Results and Discussion

The present analysis is carried out by using digitized uterine cervix images collected by National Cancer Institute (NCI) from four epidemiological studies on HPV and cervical cancer screening namely Costa Rican Natural History Study of HPV (NHS), ASCUS LSIL Triage Study (ALTS), Biopsy Study and Costa Rica Vaccine Trial (CVT) [13]. The ground truth images are neither available in the dataset nor reported in any literature. The experimentation was carried out on total 100 images from all 4 datasets including 25 images from each. These images were randomly selected from available database. The resolution of the images in ALTS and NHS is 2891 * 1973

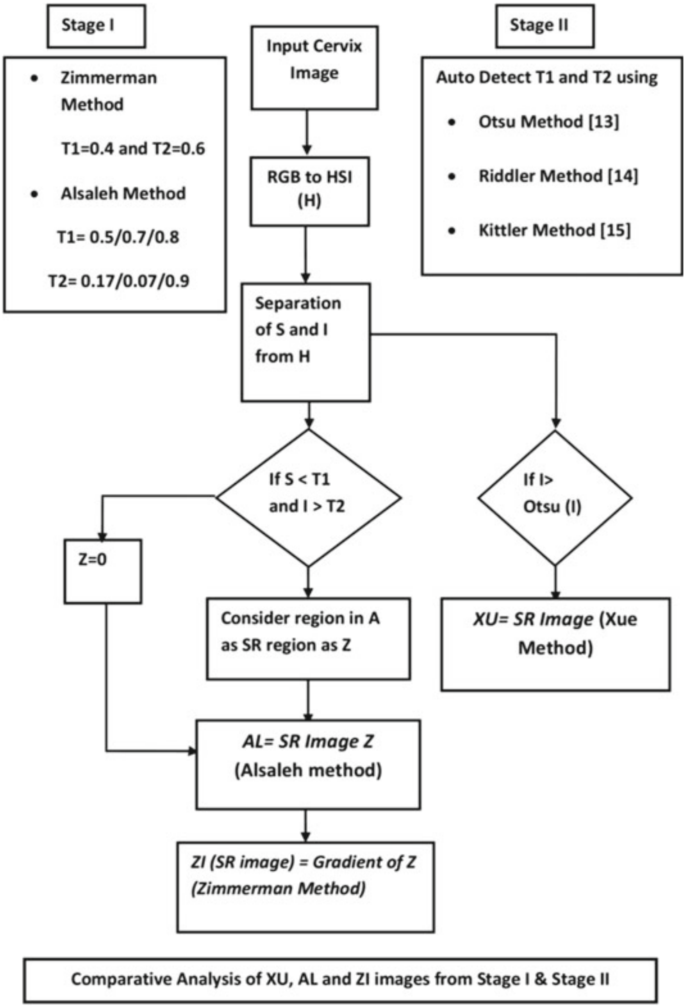

Fig. 1 Flowchart of the proposed analysis

pixels, Biopsy and CVT is 4256 * 2832 pixels. Figure 2 shows the experimental results of SR detection using Zimmerman et al. method, Xue et al. method and Alsaleh et al. method. A bright spots that can be visualized in the input image as SR pixels are detected using the three methods. The background objects like strobe must be considered as a part of noise and should be detected. Alsaleh et al. [7] method reported the detection of this background part also (Fourth row of Fig. 2). Table 2 gives the percentage of average pixels detected by state-of-art methods as SR pixels for the dataset under test. It is calculated by ratio of average of total SR pixels detected to total number of pixels present in an image database. The non-uniform percentages of SR detected pixels show a large variation amongst results of three

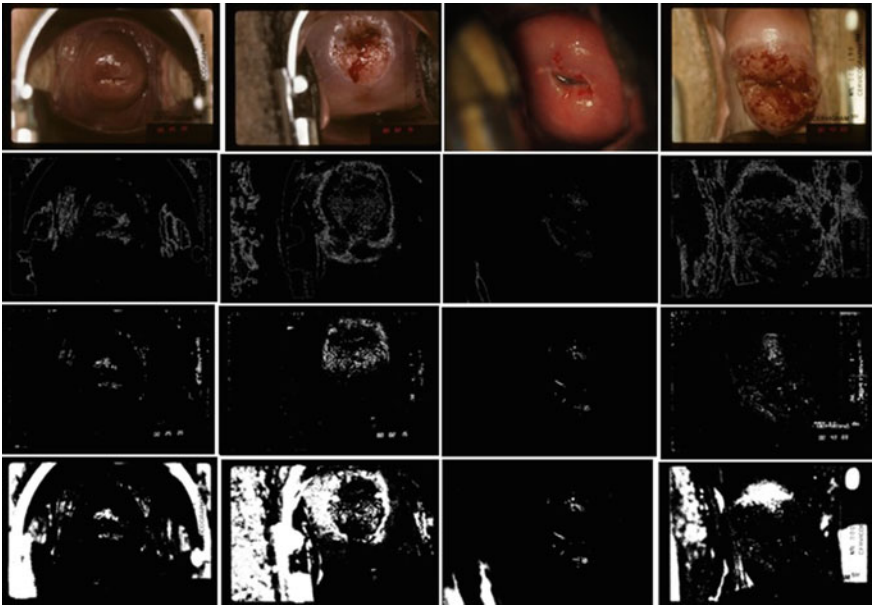

Fig. 2 Comparison of state-of-art methods for SR detection (vertically original image, Zimmerman et al. method, Xue et al. method and Alsaleh et al. method)

Table 2 Percentage of average number of pixels detected as SR on our database

Sr. No.	Method\database	ALTS	BIOPSY	CVT	NHS
1	Zimmerman et al. [5]	35.10	39.11	52.97	22.26
2	Xue et al. [6]	21	1.27	3.04	23.1
3	Alsaleh et al. [7]	31.61	26.73	40.75	20.26

state-of-art methods. This non-uniformity in percentage value affects the selection of the best state-of-art method. It can also be observed from third row of Fig. 2 that Xue et al. method extracts very few pixels as SR pixels and shows less percentage of SR pixel detection. The automatic thresholding techniques may give reason for non-uniformity.

The *Otsu, Riddler* and *Kittler* method of auto threshold detection are applied on each SR detection algorithm explained in Sect. 2.1. Table 3 gives the threshold values given by applying these automatic techniques on three methods of SR detection. The average threshold given by *Otsu* and *Riddler* in *Zimmerman* method approximates with arbitrarily defined value by Zimmerman i.e. 0.4 and 0.16. However, *Kittler* method shows some variation from arbitrary constants by Zimmerman on I image. Similar observation is seen in approximation using Otsu and Riddler for Alsaleh method, which approximates with first combination of arbitrary constants i.e. 0.5 & 0.17.

Table 3 Automatic threshold calculation for state-of-art methods

Sr. No.	Automatic thresholding algorithm	Database used in present work	Zimmerman et al. (default constants I = 0.4 & S = 0.6)		Xue et al.	Alsaleh et al. (default constants I = 0.5/0.7/0.8 & S = 0.17/0.07/0.19)	
			I	S	I	I	S
1	Otsu's method	ALTS	0.339	0.67	0.33	0.51	0.13
		BIOPSY	0.393	0.463	0.393	0.42	0.311
		CVT	0.377	0.46	0.37	0.63	0.22
		NHS	0.346	0.59	0.34	0.74	0.19
		Average	0.367	0.545	0.358	0.575	0.212
2	Cardvard and Riddler's method		0.3311	0.66	0.39	0.5	0.13
		BIOPSY	0.391	0.46	0.391	0.425	0.3
		CVT	0.37	0.46	0.37	0.63	0.22
		NHS	0.34	0.58	0.34	0.74	0.19
		Average	0.358	0.54	0.372	0.573	0.21
3	Kittler's method	ALTS	0.48	0.35	0.48	0.64	0.25
		BIOPSY	0.53	0.411	0.53	0.619	0.27
		CVT	0.5	0.5	0.5	0.63	0.17
		NHS	0.48	0.61	0.48	0.7	0.1
		Average	0.497	0.467	0.497	0.647	0.197

However, this combination fails with the use of Kittler method on I image (0.64). Thus, use of automatic threshold selection techniques justifies the need of proper selection of constant in *Alsaleh* method. This automatic calculation eliminates the database dependency on arbitrary constants reported in original method.

To validate the impact of these auto thresholding techniques, results of Riddler and Kittler methods can be visualized in Fig. 3. It can be easily visualized that, Kittler method extracts more accurate SR pixels than Riddler method. The non-detected SR pixels by Riddler method hamper the image analysis in further stages of any Computer Aided Diagnosis (CAD) system.

The qualitative analysis of SR detection technique is difficult due to unavailability of ground truth images. Kudva et al. suggested a method to compute the sensitivity of SR detection algorithm by manually marking of SR pixels for the images having practically visible SR pixels [14].

Table 4 shows the sensitivity of state-of-art methods of SR detection. It justifies the visual analysis in Fig. 2 i.e. Alsaleh et al. method is most sensitive for SR detection. It also compares the performance of Riddler and Kittler method on Alsaleh technique.

The *Xue* method violates the characteristic of SR pixel by not considering S image in its SR detection. In some cases, the Zimmerman method extracts non-SR pixels due to consideration of gradient pixels as SR pixels.

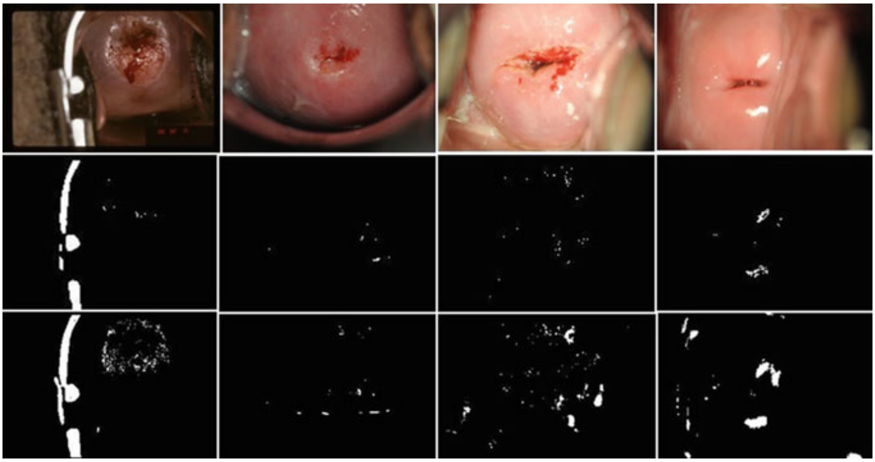

Fig. 3 Comparison of automatic threshold detection techniques (vertically original image, Riddler et al. method, Kittler et al. method)

Table 4 Sensitivity comparison of Alsaleh combined with Riddler and Kittler

Image	Zimmerman method [5]	Xue method [6]	Alsaleh method [7]	Alsaleh + Riddler method	Alsaleh + Kittler method
1	0.55	0.13	0.85	0.82	0.85
2	0.7	0.75	0.8869	0.7228	0.9
3	0.85	0.8537	0.8918	0.80	0.9363
4	0.55	0.5308	0.9469	0.8	0.94

Alsaleh method produces better results as compared to other two methods. Due to optimization of average pixel classification error rate i.e. minimum error thresholding, Kittler method outperforms over other two auto thresholding algorithms. It highlights the need of automatic selection of constant in SR detection. The use of automatic thresholding technique on *Alsaleh* method shows significant change in the SR detected pixels (Figs. 2 and 3) and increases overall accuracy. In cervix cancer treatment, its early prediction improves the chances of speedy recovery of the subject. The SR free cervix images will lead to accurate prediction and hence detection of cancerous tissues. The automatic mode of constant selection provides the edge over conventional (static) mode. The present analysis proved that the SR detection is improved with automatic selection mode. Hence, it is recommended to employ the combination of Kittler method for auto thresholding and *Alsaleh* method to fulfill the purpose of accurate SR detection.

4 Conclusion

The arbitrary selection of constants in the state-of-art methods of SR detection affects the accuracy. Hence, three automatic threshold selection techniques are applied on them. Kittler method shows maximum deviation of 0.09 & 0.14 and 0.14 & 0.02 in for threshold values of I and S images respectively. The present work proposes a combination of *Kittler's* automatic threshold selection technique and *Alsaleh* method of SR detection to extract the SRs, which gives highest sensitivity of about 0.9. In future, the present work may be extended towards automatic SR elimination and make an image suitable for further stages of early detection of cervix cancer.

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References

1. WHO cervix cancer report. http://www.who.int/cancer/prevention/diagnosis-screening/cervical-cancer/en
2. Suo J et al (2016) Fast and high-quality highlight removal from a single image. IEEE Trans Image Process 25(11):5441–5454 (2016)
3. Das A et al (2011) Elimination of specular reflection and identification of ROI: the first step in automated detection of cervical cancer using digital colposcopy. In: IEEE international conference on imaging systems and techniques, Penang, pp 237–241
4. Akbar H, Herman NS (2016) Removal of highlights in dichromatic reflection objects using segmentation and inpainting. In: International conference on robotics, automation and sciences (ICORAS), Melaka, pp 1–4
5. Zimmerman G et al (2006) Automatic detection of specular reflections in uterine cervix images. Proc SPIE 6144
6. Xue Z et al (2007) Comparative performance analysis of cervix ROI extraction and specular reflection removal algorithms for uterine cervix image analysis. Proc SPIE 6512
7. Alsaleh SM et al (2015) Automatic and robust single-camera specular highlight removal in cardiac images. In: 37th annual international ieee conference of engineering in medicine and biology society (EMBC), Milan, pp 675–678
8. Yao R et al (2010) Specular reflection detection on gastroscopic images. In: 4th international conference on bioinformatics and biomedical engineering, Chengdu, pp 1–4
9. Sezgin Mehmet et al (2004) Survey over image thresholding techniques and quantitative performance evaluation. J Electron Imaging 13(1):146–165
10. Gonzalis Woods RC (2000) Digital image processing. An imprint of pearson education, 1st edn. Edition Wesley
11. Ridler TW, Calvard S (1978) Picture thresholding using an iterative selection method. IEEE Trans Syst, Man, Cybern smc-8(8)
12. Kittler J, Illingworth J (1986) Minimum error thresholding. IEEE J Pattern Recognit 19(1):41–47 (1986)
13. Cervix Image Sharing Protocol (CISP) User Guide, NCI, Bestheta, US, September (2017)
14. Kudva et al (2017) Detection of specular reflection & segmentation of cervix region in uterine cervix images for cervical cancer screening. IRBM 38:281–291