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A COMPARATIVE STUDY OF AUTOMATED SEGMENTATION METHODS FOR CELL NUCLEUS DETECTION

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One of the most significant current discussions in the medical field is a medical image, especially on segmentation process (Mustafa, Abdul-nasir *et al*., 2017; Mustafa *et al*., 2015; Mustafa, Yazid *et al*., 2017). The segmentation of medical images such as nucleus region is a big challenging task in the image processing field and analysis due mainly to noise, shadow, random background, overlapping objects, and illumination problem (Beliz-Osorio *et al*., 2011; Genctav *et al*., 2012; Mustafa *et al*., 2014; Mustafa & Yazid 2016; Mustafa & Yazid 2017; Mustafa & Yazid 2018).

In the past decades, many researchers have been primarily concentrated and focuses on automated segmentation because of it more accurate and effective compared to the conventional methods (Genctav *et al*., 2012; Li *et al*., 2012; Quelhas *et al*., 2010). The sensitivity and correct diagnosis information are very important in order to help doctor/pathologist to analysis the patient condition. Furthermore, the automated system is a faster process to identify the patient disease compared to the old technique of using the microscope procedure (Gonzalez & Woods 2008). Recently, the nucleus segmentation has been one of the major interesting research subjects due to detecting the critical disease such as genetic and cancer problem. However, the segmentation of nucleus region is more difficult since most of the nucleus are often part of histological structures presenting complex and irregular visual aspects (Irshad *et al*., 2014).

In recent years, there has been an increasing amount of literature on discussions about the automated segmentation on the medical image. The automated system proposed basically based a new algorithm and methodology (Li *et al*., 2012). Many researchers have agreed that challenges in order to propose of automated nucleus segmentation due to the complexities of cell structures problem (Genctav *et al*., 2012; Gonzalez & Woods 2008). Osorio *et al.* (2011) published a paper in which they described a new segmentation method known as locally constrained watershed transform (Beliz-Osorio *et al.,* 2011). The technique is inspired by the Beare method (Beare, 2006) and is improved upon by eliminating the low contrast effect. The watershed transform is a segmentation technique that floods an input image gradient, which is considered as a topographic relief (Gonzalez & Woods 2008). A serious drawback with this approach is often inaccurate in case of the large overlapping area.

A number of studies have found that the overlapping cells became a big problem especially to detect the nucleus and cytoplasm region (Lu *et al*., 2013; Tareef *et al*., 2014). In the past years, many segmentation approaches were presented on nucleus segmentation, however, the majority of them cannot solve the overlapping cells issues. In 2010, a new segmentation based on Bayesian Classification experimented on the overlapped nucleus (Jung *et al*., 2010). This method involves a few step such as; perform distance transform and proposed a mixture of Gaussians. The result performance is effective and successful compared to the classical watershed, condition erosion (Yang *et al*., 2006) and adaptive H-minima transform (Cheng & Rajapakse 2009). Besides, Lu *et al.* (2013). discuss the challenges and strategies for cell segmentation under overlap and poor contrast condition. They proposed a new mathematical algorithm know as joint level set optimisation which concentrates on the overlapping boundary. The finding is consistent with the study by Tareef *et al*. (2014). They focus to solve overlapping cells based on three stages; (1) generate the superpixel by using clustering technique, (2) separate the cytoplasm and nucleus using linear classifier and (3) applied edge enhancement process and gradient thresholding. Recently, researchers have shown an increased interest in order to proposed nucleus

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detection/segmentation method (Zhang *et al*., 2014; Genctav *et al*., 2012; Li *et al*., 2012; Quelhas *et al*., 2010). Jung and Kim (2010) proposed H-minima transform in order to obtain the optimal segmentation result. However, the detection performance depends on the *h* value. In contrast, Zhang *et al*. (2014) suggest a new technique based on global and local graph cuts. Interesting, this approachable to detect cytoplasm and nucleus at the same time and more effective compared to the Mean Shift and Active contours without edges (ACWE) (Chan & Vese 2001).

In this paper, a comprehensive state-of-the-art review on the nucleus segmentation was discuss properly. A few selected segmentation approach such as Local Adaptive method, Niblack method, Bradley method, Sauvola method, Nick method and Wolf method experimented on nucleus image dataset. A few image quality assessment (IQA) such as accuracy, Peak Signal Noise Ratio (PSNR) and F-measure was obtained in order to prove the effectiveness of each segmentation technique. The objectives of this paper are to explore the advantages and drawback about medical image segmentation. Besides, this study also to find the best method and algorithm to segment the nucleus image based on six (6) types of segmentation approach.

A selected segmentation method in this experiment described in Table 1. The aim, equation, and drawback each method were explained properly. A variable parameters value of each method such as *k* was set based on the optimum segmented result. The main disadvantages of all segmentation methods are manually obtained the variable parameters and windowing sizes.

Table 1. Summary of selected segmentation methods

Method	Description	Algorithm
Niblack	To set the threshold value based on local standard deviation and local mean (Niblack 1986; Bataineh *et al.* 2011). **Disadvantage**: produces a large amount of black noise in the empty windows.	$T = m+k\sigma$ m = mean value σ = standard deviation k = –0.9
Local Adaptive	If the pixel value is below the threshold, it is set to the background value, otherwise, it assumes the foreground value (Gonzalez & Woods 2008). **Disadvantage**: requires the values of the factors k and the window size to be determined manually.	$T = \frac{\max + \min}{2}$ w = local windowing size (40 by 40) k = local threshold (0.15)
Bradley	The key idea of the algorithm is that every image's pixel is set to black if its brightness is *T* percent lower than the average brightness of surrounding pixels in the window of the specified size, otherwise it is set to white (Bradley & Roth 2011). **Disadvantage**: still fails to solve the extreme illumination	$T = m\left(1-\frac{k}{100}\right)$ m = mean value k = 12
Sauvola	To solve the problem of black noise depending on the impact on the standard deviation value by using a range of gray-level values in the images (Bataineh *et al.* 2011; Sauvola *et al.* 1997; Sauvola & Pietikäinen 2000). **Disadvantage**: failed if the contrast between the foreground and background is small or if the text is in thin pen stroke text.	$T = m\left(1 - k\left(1 - \frac{\sigma}{R}\right)\right)$ R = gray-level (128) m = mean value σ = standard deviation k = 0.1
Nick	To improve the Niblack method (black noise) and Sauvola method (low contrast) by shifting the thresholding value downward (Khurshid *et al.* 2009; Bataineh *et al.* 2011). **Disadvantage**: still fails when the contrast is too small or the text is in thin pen stroke text.	$T(x,y) = m + k\sqrt{\frac{(I^2 - m^2)}{N}}$ m = mean value k = –0.13 I = pixel intensity N = image size
Wolf	To localize artificial text in images and videos using a measure of accumulated gradients and morphological processing. The quality of the localized text is improved by robust multiple frame integration (Wolf *et al.* 2003). **Disadvantage**: not work properly on the image which contents many structures such as text image and retinal image.	$T = (1-a)m + aM + a\frac{s}{R}(m-M)$ m = mean value s = standard deviation a = gain parameter M = image size minimum value of the gray levels R = maximum value of the standard deviations

In this work, 25 cell images from online dataset were tested. The images contain various low contrast, non-uniform illumination, and background problem. All the processed images are in greyscale images and the size of each image is 250 × 150 pixels, 72 dpi, and 8-bit depth. All the programs were written in MatLab R2009a from an Asus laptop with AMD Athlon^{TM} II P320 Dual-Core Processor 2.10GHz and 3.00GB RAM. In this experiment, all the segmentation methods unsuccessful especially when to deal with the contrast problem cause the intensity level on nucleus area approximate to the intensity level of background images. Figure 1 shows the resulting images after applying the segmentation methods. Based on observation, Niblack method unsuccessful in detecting the nucleus region properly, since the wolf method shows the impressive result compared to other methods.

In order to find the best segmentation methods, a few Image Quality Assessment (IQA) was calculated. The result of IQA was present on Table 2. From the data in Table 2, it is apparent that all selected method gave the satisfied result. Mathematically, it has been proven that higher the Accuracy, PSNR, and F-measure represent the effectiveness of approaches (Yazid & Arof 2013; Pratikakis *et al*., 2011). The Wolf method achieved the highest result for all three (3) IQA evaluation (Accuracy=99.731, PSNR=29.325 and F-measure= 92.933).

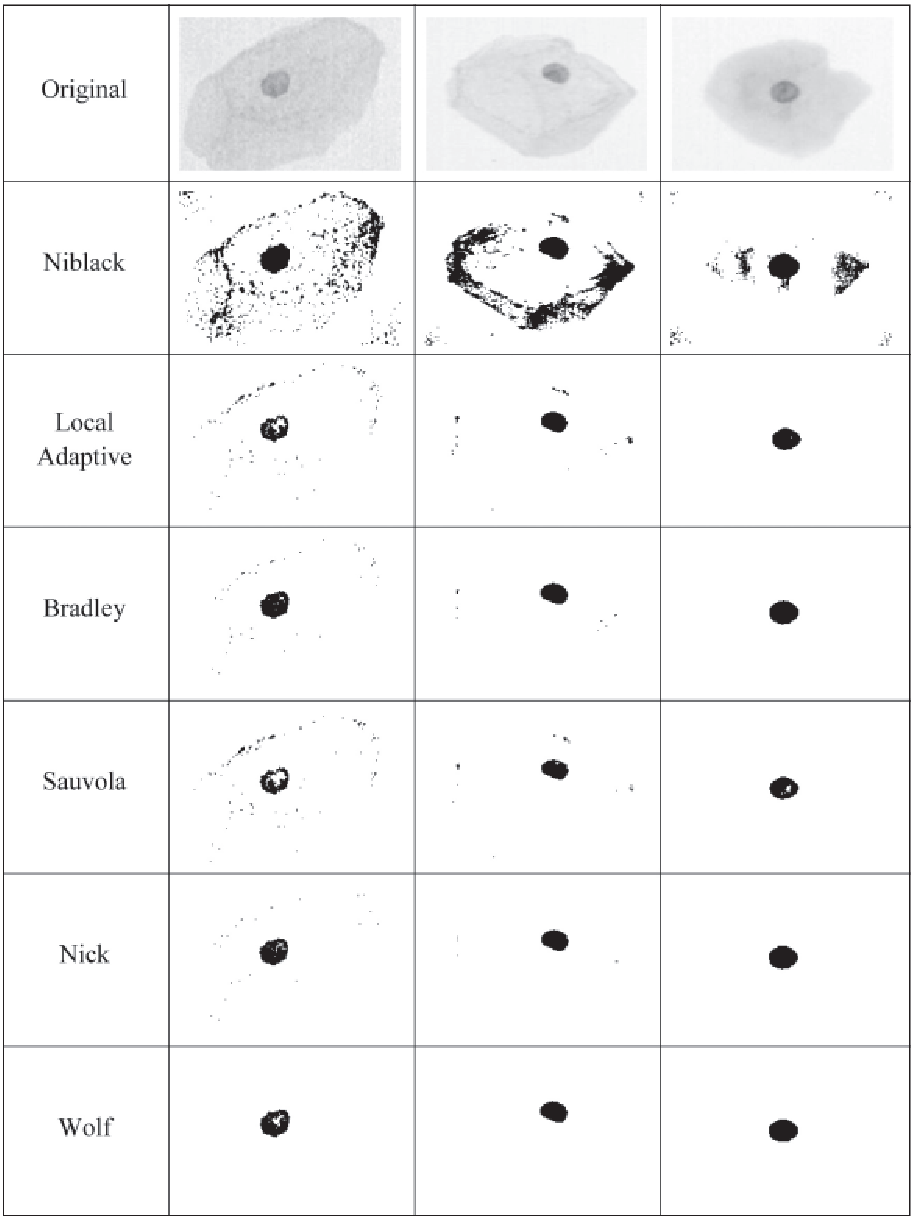

Fig. 1. Comparison of 6 types of segmentation approaches.

Table 2. Comparison segmentation result based on IQA

Method	Image Quality Assessment (IQA)		
	Accuracy (%)	PSNR (dB)	F-Measure
Niblack	93.725	12.196	33.804
Local Adaptive	99.026	22.187	76.705
Bradley	99.618	27.478	90.039
Sauvola	99.226	23.093	78.427
Nick	99.673	27.497	90.709
Wolf	99.731	29.325	92.933

The key step of a computer-assisted screening system that aims early diagnosis of cancer is the accurate segmentation of cells especially nucleus region. In this review, six (6) types of segmentation approach experimented on 25 sample cell images. This study set out to determine and find the best approach in order to segment the nucleus region. The results of this research show that the Wolf method successful and good performance (Accuracy =99.731%, PSNR 29.325 dB and F-Measure= 92.933) in detecting nucleus compares others methods. Besides, other methods such as Nick, Sauvola, and Bradley method present the satisfied result. The findings from this review make several contributions to the current literature. First to find the best approach to detect the nucleus. Second, to identify the advantages and drawback of each segmentation methods. Third, give the direction to other researchers to propose a new effective method or algorithm. The future review should concentrate on the investigation of segmentation on overlapping cells.

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