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A Colour Space Based Detection for Cervical Cancer Using Fuzzy C-Means Clustering

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ABSTRACT

This research presents a colour segmentation method using Hue, Saturation, Value (HSV) colour space based on fuzzy c-means clustering (FCM) to segment nucleus from single cell Pap smear images. Nucleus is a structural part of cell which can indicate whether a cell is normal or abnormal. This research aims to analyze the performance of colour space in the segmentation process. Pap smear images were segmented in HSV colour space by using fuzzy c-means clustering technique. Compared with segmentation process directly on HSV channel, the segmentation of each channel in space H, S and V were proposed. The segmentation results on each channel that has been applied roundness detection subsequently merged as the final segmentation and labeled as a nucleus. This research used 70 single cell Pap smear images taken in harlev dataset to examine the proposed segmentation method. The calculation of segmentation performance used the measurement based on precision, recall, and Zijdenbox Similarity Index (ZSI). The result showed that the proposed method generated precision, recall, and ZSI by 93%, 94%, and 93%.

CCS Concepts

• Computing methodologies → Computer graphics → Image manipulation → Image processing

Keywords

Colour segmentation; nuclei segmentation; HSV colour space; FCM; Pap smear images.

1. INTRODUCTION

According to data from World Health Organization (WHO) in 2012, about 270.000 women died of cervical cancer in which more than 85% of these deaths occur in low- and middle-income countries [1].

In 2013, Indonesia, according to Health Department is a country where cervical cancer stands in the first rank of most cancer patients in women with a prevalence of 0.8% or 98.692. Riau Islands Province, North Maluku Province, and Special Region of Yogyakarta have the highest prevalence of cervical cancer which is 1.5%. It is due to the lack of health care infrastructure in the

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ICBBS '17, June 22-24, 2017, Singapore, Singapore
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ACM ISBN 978-1-4503-5222-2/17.06...\$15.00.
DOI: <https://doi.org/10.1145/3121138.3121196>

less developed regions [2].

Pap smear is a screening method for early detection on cervical cancer through the detection of morphological changes in cancer cells. This method has helped reduce 70% of mortality in developed countries [3]. Although pap smear is the best screening in early detection, an error detection becomes a great concern. Generally, the level of accuracy of cervical cancer diagnosis is about 60% to 70% [4]. In addition, the limitation of pathologist to analyze the great number of pap smear samples still conventionally causes the human error such as fatigue, so it makes the image segmentation of the cervical cells has attracted attention in the medical world [5].

The segmentation of cervical cells on pap smear images is an important step in getting information of the morphological, colour, and cells text to differentiate between normal and abnormal cells. The cell nucleus is a structural part of the cell that can show significant changes when the cell is exposed to the disease. Most malignant characteristics of cell contain in the cell nucleus so that the cell nucleus is widely used in cell classification standard such as The Bathesda System (TBS) [6]. Because of the importance of the nuclei, so the cell nuclei segmentation accuracy becomes the important task in developing the detection system of cervical cancer.

Some studies related to the segmentation of nuclei had been done before. Chankong et al. used a segmentation method of patch based fuzzy c-means clustering (FCM) for the segmentation in the region of nucleus, cytoplasm, and background. Segmented images using a dataset of ERUDIT, LCH, and harlev. The results showed that the nuclei segmentation in harlev dataset gave precision, recall, and ZSI by 85%, 83%, and 80% [7]. Nuclei segmentation method was also conducted by Tang et al. using Intersection of Optical Model (ICM) and Particle Swarm Optimization (PSO) to optimize the parameters in the ICM. The method was applied to images taken randomly in harlev dataset. To analyze the performance of the proposed method, ZCI calculation was used. The result showed 91% [8].

This research presented a method of colour segmentation using HSV colour space based on fuzzy c-means clustering (FCM). Colour image segmentation has the ability to improve the analysis process because the colourful images are more accommodating information needed [7]. It underlies this research by using a colour-based segmentation. The main consideration in the colour segmentation is to choose the right colour space. HSV colour space has been widely used because it is more similar to how the human perceives colour so we chose this colour space [9]. We also used fuzzy c-means clustering in the image segmentation process because clustering method is very efficient when dealing

with image segmentation. To analyze the method performance, we used precision, recall, and ZSI.

2. MATERIALS AND METHODS

2.1 Dataset

A colour segmentation method based on fuzzy c-means clustering (FCM) to separate the nuclei from a single cell Pap smear is proposed. The segmentation method implemented in Harlev dataset consisting of 917 single cells Pap smear images. Pictures taken by the pathologist using a microscope then be classified into 7 classes [10]. In this work, 70 images selected randomly in each class to be segmented, then the segmentation results will be compared with ground truth to see the performance of proposed segmentation method.

2.2 HSV Colour Space

HSV Colour Space stands for hue, saturation, and value. Hue is the angle in the range $[0, 2\pi]$ relative to the red axis where the red at an angle of 0, green at an angle of $2\pi/3$, blue at an angle of $4\pi/3$ and red again at an angle of 2π . Saturation is the purity of hue colour associated with the white colour and is calculated as the radial distance from the central axis with a value between 0 in the center to 1 at the outer surface. If saturation changes from 0 to 1 so the colour perception changes from gray to the purest form of colour represented by its Hue. Value is the amount of light that illuminates the colour with a percentage range [0 to 100]. For example, when the hue colour is red and the value is high then the colour looks bright, and if the value is low, it will look dark [9].

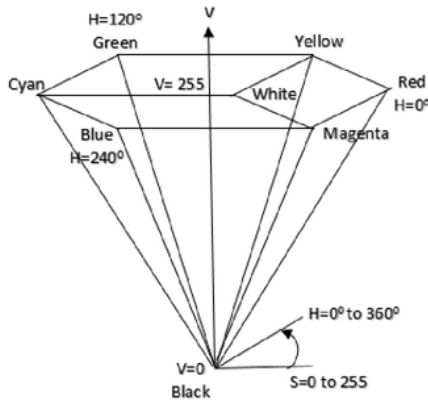


Figure 1. Diagram of HSV colour space.

The conversion of RGB to HSV used the following transformation method in (1) [11].

For example $\max = \text{MAX}(r, g, b)$, $\min = \text{MIN}(r, g, b)$, and $\delta = \max - \min$, so:

$$h' = \begin{cases} \frac{g-b}{\delta} & r = \max \\ 2 + \frac{(b-r)}{\delta} & g = \max \\ 4 + \frac{(r-g)}{\delta} & b = \max \end{cases} \quad (1)$$

To obtain the HSV color space component used (2):

$$h = h' \times 60; s = \frac{\delta}{\max}; v = \max \quad (2)$$

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2.3 Fuzzy C-Means Clustering (FCM)

Fuzzy c-means clustering is one of clustering methods to determine the membership degree of an element of the data into one or more cluster groups. Let a dataset $X = (X_1, X_2, \dots, X_N)$ will be partitioned into cluster c , then to minimize the cost function using (3) as follows [12]

$$J = \sum_{j=1}^N \sum_{i=1}^c u_{ij}^m \|x_j - v_i\|^2 \quad (3)$$

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Where, u_{ij} represents the membership of data X_j in the cluster i , V_i is the center of cluster i while m is fuzzy partition matrix exponent, where $m > 1$. The function of membership and cluster center used (4) and (5) as follows [10].

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{\|x_j - v_i\|}{\|x_j - v_k\|} \right)^{2/(m-1)}} \quad (4)$$

and

$$v_i = \frac{\sum_{j=1}^N u_{ij}^m x_j}{\sum_{j=1}^N u_{ij}^m} \quad (5)$$

The probability of fuzzy c means clustering depends only on pixel distance of each cluster center, which indicates the pixel ownership in a particular cluster. The membership value is high when the pixel is close to the cluster center while the membership value is low when pixel is far from the cluster center.

Table 1. Parameter setting in FCM

Parameter	Value
m	1.15
Maximum number of iteration	100
Minimum of improvement	$1e-8$

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FCM parameter values can be seen in Table 1. In Table 1, m is fuzzy partition matrix exponent. This parameter function is to control the degree of fuzzy overlap which refers to fuzzy boundaries between clusters. Clustering process will stop when it has reached the maximum number of iteration, or when the iteration value approaches the minimum value of improvement.

2.4 Evaluation Measures for Segmentation

The segmentation performance is measured based on detected pixel which then is compared with ground truth. This calculation used precision and recall, where True Positive (TP), False Positive (FP), and False Negative (FN) will be entered into (6) and (7) as follows [13].

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{\text{No. of correctly detected pixel}}{\text{No. of all detected pixels}} \quad (6)$$

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{\text{No. of correctly detected pixel}}{\text{No. of all pixels in the ground truth}} \quad (7)$$

This research also used the index calculation called Zijdenbox Similarity Index (ZSI). A good segmentation give the value of ZSI which is greater than 0.7 which means segmentation boundary was detected and ground truth was very suitable. The ZSI used (8) as follows [12]

$$ZSI = \frac{2TP}{2TP + FP + FN} \quad (8)$$

30 Nuclei Segmentation Using Colour Space Based on Fuzzy C-Means Clustering

In this research, the segmentation process aimed to separate nucleus from cell using color segmentation method. The method is colour space based on fuzzy c-mean clustering (FCM). The process of segmentation image was showed in Fig. 2.

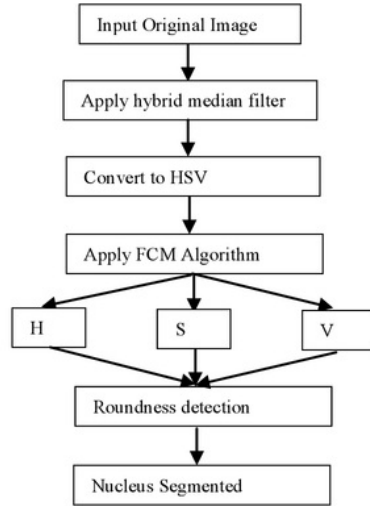


Figure 2. The diagram of proposed method

The stage of segmentation is an important stage to obtain a spatial information against the required object. In the segmentation process, the input in the form of single cell Pap smear images before being converted applied hybrid medianfilter first to eliminate the noise of original image before being processed.

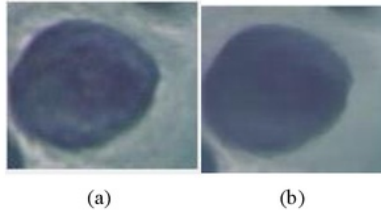


Figure 3. Picture (a) is original image and (b) image after applied hybrid median filter

Furthermore, the images were converted using HSV color space.

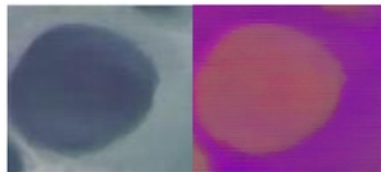


Figure 4. Image hybrid median filter is converted to HSV channel

Converted images then were segmented by using fuzzy c-means clustering (FCM), FCM will classify pixels that have similar features to its neighbors. Compared with the segmentation process directly on HSV channel, the segmentation of each channel in the space H, S, and V were preferred. The segmentation on each channel will provide the optimum pixel value which close to the center value of each channel component without ignoring feature pixels on another channel space. After each channel was segmented into 3 clusters, the next process was determined cluster which has dominant pixels value which close to center value to represent each channel.

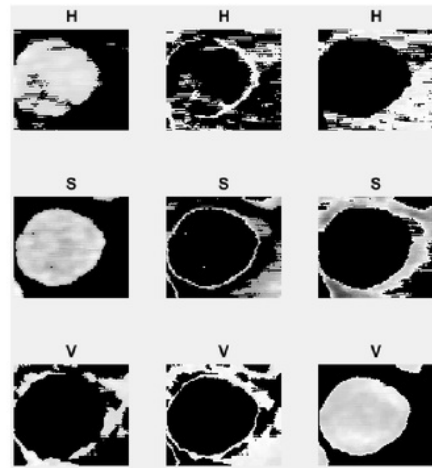


Figure 5. Clustering result of each channel HSV

Each cluster representative will be extracted using feature roundness for roundness detection process. Furthermore, each cluster of each channel which had passed roundness detection process will be merged into the final segmentation results.

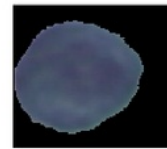


Figure 6. Segmentation Result

3. RESULT

Segmentation method applied on 70 12p smear images selected randomly on each class namely normal superficial, normal intermediate, normal columnar, mild (light) dysplasia, severe dysplasia, moderate dysplasia, and carcinoma in situ. The performance of proposed method calculated using the measurement based on precision, recall, and ZSI. Segmentation measurement results will be compared with the research method that had been done by previous researchers. Some examples of segmentation simulation results on each class can be seen in Table 2.

The performance measurement of method based on precision, recall, Zijdenbox Similarity Index (ZSI) is available in Table 3, in addition the results from the previous studies using patch based fuzzy c-means clustering (FCM) and Intersection Cortical Model (ICM) method is available as a comparison.

Table 2. Segmentation result

	Original Image	Image Segmented
5 Normal Superficial		
Normal Intermediate		
Normal Columnar		
Mild (Light) Dysplasia		
Severe Dysplasia		
Moderate Dysplasia		
Carcinoma in Situ		

Table 3. Evaluation measures of segmentation (mean±std)

		Precision	Recall	ZSI
Colour space based FCM	Sup squa	0.86 ± 0.14	0.91 ± 0.14	0.87 ± 0.09
	Inter squa	0.88 ± 0.06	0.96 ± 0.05	0.91 ± 0.02
	Columnar	0.95 ± 0.05	0.98 ± 0.02	0.96 ± 0.02
	Mild dysp	0.96 ± 0.03	0.97 ± 0.02	0.96 ± 0.01
	Severe dysp	0.96 ± 0.03	0.92 ± 0.06	0.94 ± 0.03
	Mod dysp	0.98 ± 0.01	0.89 ± 0.08	0.93 ± 0.04
	CIS	0.95 ± 0.06	0.93 ± 0.05	0.94 ± 0.03
	Average	0.93 ± 0.03	0.94 ± 0.03	0.93 ± 0.02
Patch based FCM	Sup squa	0.95 ± 0.12	0.75 ± 0.33	0.78 ± 0.29
	Inter squa	0.98 ± 0.03	0.82 ± 0.25	0.86 ± 0.21
	Columnar	0.88 ± 0.20	0.78 ± 0.25	0.79 ± 0.19
	Mild dysp	0.80 ± 0.31	0.86 ± 0.26	0.79 ± 0.28
	Severe dysp	0.79 ± 0.28	0.88 ± 0.21	0.79 ± 0.25
	Mod dysp	0.81 ± 0.25	0.88 ± 0.19	0.81 ± 0.21
	CIS	0.70 ± 0.29	0.88 ± 0.23	0.75 ± 0.25
	Average	0.85 ± 0.21	0.83 ± 0.25	0.80 ± 0.24
ICM	Average	-	-	0.914

Table 3 showed that colour segmentation method using colour space based fuzzy c-means clustering (FCM) which was proposed obtained better results with average of precision, recall, ZSI by 93%, 94%, and 93% compared with patch method based on fuzzy c-means clustering (FCM) with the results of 85%, 83%, and 80% and Intersection Cortical Model (ICM) method with ZSI amounted to 91%.

4. CONCLUSION

The accuracy of segmentation is an important to analyze pap smear images. The nuclei segmentation of single cell pap smear images had been done in this research. A colour segmentation method in HSV colour space based fuzzy c-means clustering (FCM) has been proposed. The segmentation method applied to 70 Pap smear images taken randomly in each class namely normal superficial, normal intermediate, normal columnar, mild (light) dysplasia, severe dysplasia, moderate dysplasia, and carcinoma in situ. Furthermore, each segmented sample measured using calculation based precision, recall, and ZSI. This research compared with previous segmentation method based grayscale namely patch based on fuzzy c-means clustering (FCM) and Intersection Cortical Model (ICM). The result showed that colour segmentation in HSV colour space based FCM was better than previous methods with precision, recall, and ZSI by 93%, 94%, and 93%. Meanwhile, patch based on fuzzy c-means clustering (FCM) obtained 85%, 83%, and 80% and ZSI Intersection Cortical Model (ICM) obtained 91%. It showed that colour segmentation in HSV color space was closer to the ground truth, it means that color segmentation has a better segmentation capabilities compared with the segmentation of grayscale.

5. ACKNOWLEDGMENT

This work is using the data from: Pap smear Benchmark Data For Pattern Classification J. Jantzen I, J. Norup, G. Dounias, and B. Bjerregaard, University Hospital Dept. of Pathology Herlev Ringvej 75, DK-2730 Herlev, Denmark. This work is also supported by AIMP research group of Hasanuddin University

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