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Ensembles of Normalization Techniques to Improve the Accuracy of Otsu Method

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Abstract

Otsu method is a global thresholding method that uses between class variance as a discriminant criterion in order to maximize the separation between background and foreground of an image. However, there are problems of biasness in Otsu method. These problems are caused by the differences in class variances. The threshold value obtained by Otsu method will be bias towards the larger class variance component. Hence, in this paper, a new variant of Otsu method by using normalization techniques and their ensembles is proposed. By using normalization techniques, grey level values will be transformed into a smaller range in feature space and this will affect Otsu method as this method depends on grey level values. The domination of certain grey level values also will be eliminated. Rank filtering has been applied to eliminate noises and ensemble approaches of normalization techniques are utilized to increase the performance of the proposed method. Ensemble approaches namely Maximum Variance, Majority Voting, Product Rule, Addition Rule and Average Rule have been applied on the binary images obtained. From the experiment on 20 retinal images randomly selected in 50 runs from DRIVE and STARE databases, Maximum Variance shows the most significant result that is 95.39% accuracy. While from the experiment on 15 document images randomly selected in 50 runs from DIBCO2009 and DIBCO2011 databases, Average Rule shows the most significant result that is 97.17% accuracy. This indicate the use of ensembles of normalization techniques can give promising result to improve Otsu method.

Keywords: segmentation, thresholding, Otsu method, normalization techniques, ensemble approaches

1 Introduction

Segmentation divides an image into different parts containing each pixel with similar attributes. In order to make image analysis and interpretation to be meaningful and useful, the parts should be related strongly to depicted objects or features of interest. The first step of significant segmentation is to transform a grey scale or color image as low-level image processing into one or more other images to high-level image description in terms of features, objects, and scenes. Reliability of segmentation results will affect the success of image analysis. Hence, it is a very challenging problem to get an accurate partitioning of an image.

One of the widely used techniques in image segmentation is to threshold an image automatically. Thresholding is a simple method but effective to separate object from background. An optimal threshold value will be automatically selected based on grey level value distribution to separate object of interest from the background [1]. Thresholding algorithms have been divided into six groups namely histogram shape information, measurement space clustering, histogram entropy information, image attribute information, spatial information and local characteristics [2]. Computer vision applications have used thresholding techniques widely such as document binarization [3][4], automatic visual inspection of defects [1], medical image segmentation [5] , detection of eye positions [6].

In general, automatic thresholding has been roughly classified into global and local thresholding [1] . A single threshold value will be selected for entire image in global thresholding while local thresholding will select multiple threshold values where each is optimized for a small region in the image. Global method can minimize the computational cost and the noise in resultant images with faster execution time [7]. However, the whole binary process will be affected by local noise and changes in partial characteristics of the image. As a result, this can cause under or over thresholded images.

Among the global thresholding techniques, Otsu method had been widely referenced. Otsu method [8] used discrimination criterion namely between-class variance in order to automate threshold selection by maximizing the separation of the resultant classes in gray levels. However, Otsu method is found to have problems with binarization due to the differences in class variances [9]. Hence, the obtained threshold will be biased towards the larger class variance component. Characteristics of Otsu threshold value have been analyzed by [10] and they found the Otsu threshold value is biased toward the class with larger variance. This problem will lead to misclassification of pixels belonging to a class into the other class which have smaller variance. Otsu method also uses an exhaustive search to evaluate the discrimination criterion for maximizing the between class variance. Hence, Otsu method takes too much time for multilevel threshold selection [11].

Otsu method uses between class variance as discrimination criterion. In order to calculate between class variance, each grey level values will be used. This shows that variance is sensitive towards grey level values. Any changes happen in grey level values will affect variance values. Normalization is a process that transform values of different parameters of an image to more convenient values. By using normalization techniques, grey level values will be transformed into a smaller range in feature space and this will affect Otsu method as this method depends on grey level values. Furthermore the domination of certain values can be eliminated. Rank filtering will be used to eliminate noises. Then, ensemble of normalization techniques are utilized to enhance the final performance of the Otsu method as it can maintain the strength and eliminate the weaknesses of each normalization techniques. The ensemble approaches will exploit all the information available in the outputs of all normalization techniques. Utilizing the idea of integrating advantages of normalization technique and ensemble approaches, an algorithm is proposed to improve Otsu method. The rest of the paper is organized as follows: Section 2 reviews some related works about Otsu method. Section 3 describes some fundamental principles on normalization techniques and Otsu method. Section 4 describes proposed method and experimental results are shown in Section 5. Section 6 will discuss and conclude this paper.

2 Related Works

There are a lot of improvements done by researchers on Otsu method. Recursive Otsu algorithm is used by [12] to find threshold value in order to reduce the computational complexity of the multilevel threshold when compared with conventional Otsu method. They have used look-up table to evaluate pre-calculated between class variance. But, when the number of thresholds increases, the problem of long duration processing time still occurs. In a research done by [10], it has been proved that the threshold obtained from Otsu method is equal to the average of the mean levels of two classes partitioned. They have improved Otsu method by giving constrain to the search range of grey levels. Otsu method follow basic principle of using Gaussian distributions for the estimation of linear grey level histograms. But [13] claimed that a better model is low-bandwidth Gaussian randomized procedure. This is because the response of image transmission and acquisition system follows low-bandwidth frequency response. As a result, the object and the background obey Rayleigh distributions. By using this model, high segmentation precision is obtained. Otsu method have used the sample mean and the sample standard deviation to estimate location and dispersion. Since median is one of the robust estimator of location, [14] have introduced median-based approaches to image thresholding. They have proposed the extension of Otsu method and the extension of Kittler and Illingworth's minimum error thresholding by using the median values. However, this approach have two limitations that are the multi-modality of the criterion functions and the other one is the extreme results of the obtained threshold values. Another technique to improve Otsu method is done by [15] by changing the mean value with variance value. In this technique, an assumption have been used that the probability for the threshold value should be divided by two that is for background and foreground. Based on this, weight have been applied differently for background and foreground in Otsu method. The images obtained are clearer compared to using Otsu method. Three dimensional (3D) Otsu thresholding have been used by [16] in order to improve Otsu method. 3D Otsu algorithm have been optimized by using shuffled frog-leaping algorithm. A widened local search is obtained by applying the modifications. Thus, the performance have been improved and premature convergence can be prevented. Otsu method also have been widely used in segmenting medical images. To process abnormal brain magnetic resonance (MR) image, [17] have used Otsu method and morphological operations. Then, the segmented resultant images are fused with the original MR image and hence satisfactory results are obtained. Another algorithm that used the help of iterative Otsu thresholding scheme and mathematic morphological processing is done by [18] to find a rough border of the pectoral muscle. An accurate segmentation of the pectoral muscle is obtained when employing a multiple regression analysis. Experimental results show that the pectoral muscle extracted by using this method is approximately same as extracted by an expert radiologist.

3 Theoretical Background

We first described the fundamental principle of the methods used in the study.

Normalization Techniques

Three normalization techniques have been used and they are L1-norm, L1-sqrt and L2-norm [19].

a. L1-norm , $\boldsymbol{v} \to \boldsymbol{v}/(\|\boldsymbol{v}\|_1 + \boldsymbol{\epsilon})$ where $\|\boldsymbol{v}\|_1 = \sum|\boldsymbol{x_n}|$.

b. L1-sqrt, apply L1-norm and then followed by $\to \sqrt{\boldsymbol{v}/(\|\boldsymbol{v}\|_1 + \boldsymbol{\epsilon})}$.

c. L2-norm, $\boldsymbol{v} \to \boldsymbol{v}/\sqrt{(\|\boldsymbol{v}\|_2^2 + \boldsymbol{\epsilon}^2)}$ where $\|\boldsymbol{v}\|_2^2 = \sum \boldsymbol{x_n}^2$.

where $\boldsymbol{v}$ is the column vector of the grey level values.

In our work done in [20], we have used 4 normalization techniques that are L1-norm, L1-sqrt, L2-norm and L2-Hys. However, L2-Hys is found to produce same results as L2-norm but it consume a lot of time. Then, L2-Hys is excluded from this experiment.

Rank Filtering

For a particular window, for example 3 x 3 window, neighborhood pixels are being arranged in ascending order. From this ordering, every pixel will be replaced by selecting the required rank for the ordered values that have been developed. The placement of the value within this ordered set is referred as the rank. The process will be:

a. For *D* x *D* window, the pixel can be ordered as follows:

$$G_1 < G_2 < G_3 < \cdots < G_{D^2}$$

and $G_1, G_2, \ldots, G_{D^2}$ are grey level values.

b. A value will be selected from a particular position. Select a value from a particular position in the list to use as the new value for the pixel.

Rank filtering is nonlinear filters. According to [21], nonlinear filters are based on ordered statistics. With the presence of impulsive noise, nonlinear filters have excellent robustness properties. Nonlinear filters can preserve edge information and the computation is easy and fast.

Otsu Method

An image can be represented in *T* gray levels, [1, 2, …, *T*]. The frequency of pixels at level *l* is denoted by f_i and the total frequency of pixels is $N = f_1+f_2+f_3+\ldots+f_l$. The probability of occurrence of pixels at level *l* is defined as

$$p(l) = \frac{f_l}{N} \tag{1}$$

The entire image will have the average gray level as

$$\mu_T = \sum_{l=1}^{L} l p_l \tag{2}$$

For two classes that is for single thresholding, C_1 and C_2 will denote pixels at levels [1, 2, 3, …, *t*] and [*t*+1, *t*+2, …, *L*] respectively. The probabilities of the class C_1 and C_2 will be

$$\omega_1 = \sum_{l=1}^{t} p_l = \omega_t \tag{3}$$

and $$\omega_2 = \sum_{l=l+1}^{L} p_l = 1 - \omega_t \tag{4}$$

The mean gray levels of the two classes are computed as

$$\mu_1 = \sum_{l=0}^{t} l p_l / \omega_1 \tag{5}$$

and $$\mu_2 = \sum_{l=t+1}^{L} l p_l / \omega_2 \tag{6}$$

[3] have showed that by maximizing between-class variance

$$\sigma_B{}^2(t) = \max(\sigma_B{}^2(t)) \quad \text{for } 1 \le t \le L \tag{7}$$

where

$$\sigma_B{}^2(t) = \omega_1(\mu_1 - \mu_T)^2 + \omega_2(\mu_2 - \mu_T)^2 \tag{8}$$

optimal threshold *t* can be obtained.

4 Proposed Method

Preprocessing is the process of improving visual display of images. In this experiment, there will be two types of images to be used i.e. retina and document images. Retinal images are color images that consist three different channels that are blue, red and green. Green channel is used for further preprocessing since it contain a lot of useful information [22]. Preprocessing for retinal images involve several steps which include sharpening, contrast enhancement and Gaussian filter. For document images, only Gaussian filter will be applied for preprocessing step. In the proposed method, three normalization techniques are applied to the images that are L1Norm, L1Sqrt and L2Norm. After applying normalization techniques, rank filtering will be used to eliminate noises and then, Otsu method will be applied. At this stage, three binary images will be obtained. For each binary image, each pixel has been compared and their values are determined.

In order to produce final images, ensemble approaches method have been applied. The first method is, applying the same principle as Otsu method that is by selecting the binary images with maximum between class variance (Maximum Variance) that is

$$\mathbf{max}(\boldsymbol{\sigma_{B_1}}^{\mathbf{2}}(\boldsymbol{t}), \boldsymbol{\sigma_{B_2}}^{\mathbf{2}}(\boldsymbol{t}), \boldsymbol{\sigma_{B_3}}^{\mathbf{2}}(\boldsymbol{t})) \tag{9}$$

The second method is by applying Majority Voting method. Majority Voting will combine the best action of each normalization techniques and bases its final decision on the number of times an action is preferred by each normalization techniques. For each pixel, if the number of 0's is higher than the number of 1's, then 0 will be placed in that particular location and vice versa. The comparison will be made for each location of the pixel of the image.

$$\max(n(0), n(1)) \tag{10}$$

The third method is by applying weights to each binary images. Average accuracy for each normalization technique will be determined first before assigning weights. Normalization technique that give higher average accuracy will be given higher weight while normalization technique that give lower average accuracy will be given lower weight. Then, the weight will be combined for each binary images obtained from each normalization techniques by applying these rules for any location of the pixel (*i*,*j*):

Product Rule – each weight will be multiplied for a particular pixel in each location for three binary images. If the weight for 0's is higher than the weight of 1's then, 0 will be placed in that particular location and vice versa.

$$\text{For 0: } \prod_{k=1}^{3} \boldsymbol{w_{0k}}$$
$$\text{For 1: } \prod_{k=1}^{3} \boldsymbol{w_{1k}} \tag{11}$$

Addition Rule – each weight will be added for a particular pixel in each location for three binary images. If the weight for 0's is higher than the weight of 1's, then 0 will be placed in that particular location and vice versa.

$$\text{For 0: } \sum_{k=1}^{3} \boldsymbol{w_{0k}}$$
$$\text{For 1: } \sum_{k=1}^{3} \boldsymbol{w_{1k}} \tag{12}$$

Average Rule – the average of each weight for a particular pixel will be calculated in each location for three binary images. If the average weight for 0's is higher than the average weight of 1's, then 0 will be placed in that particular location and vice versa.

$$\text{For 0: } \frac{1}{3}\sum_{k=1}^{3} \boldsymbol{w_{0k}}$$
$$\text{For 1: } \frac{1}{3}\sum_{k=1}^{3} \boldsymbol{w_{1k}} \tag{13}$$

By applying ensemble approaches, namely Maximum Variance, Majority Voting, Product Rule, Addition Rule and Average Rule, five new binary images will be obtained. These new images will be compared with ground truth images. In order to evaluate the performance of the proposed method, we will compare the results with standard Otsu method. The flowchart for the proposed method is shown in Figure 1.

5 Experiment and Results

Material

Four publicly available databases namely as DRIVE [25], STARE [26], DIBCO2009 [27] and DIBCO2011 [28] will be used to evaluate the performance of the proposed method. DRIVE and STARE databases comprise retinal images and were used to evaluate the blood vessel segmentation. While DIBCO2009 and DIBCO2011 databases comprise handwritten and printed documents and were used to evaluate document image binarization. These databases are chosen since they provide manual segmentation for performance evaluation and have been widely used by other researchers.

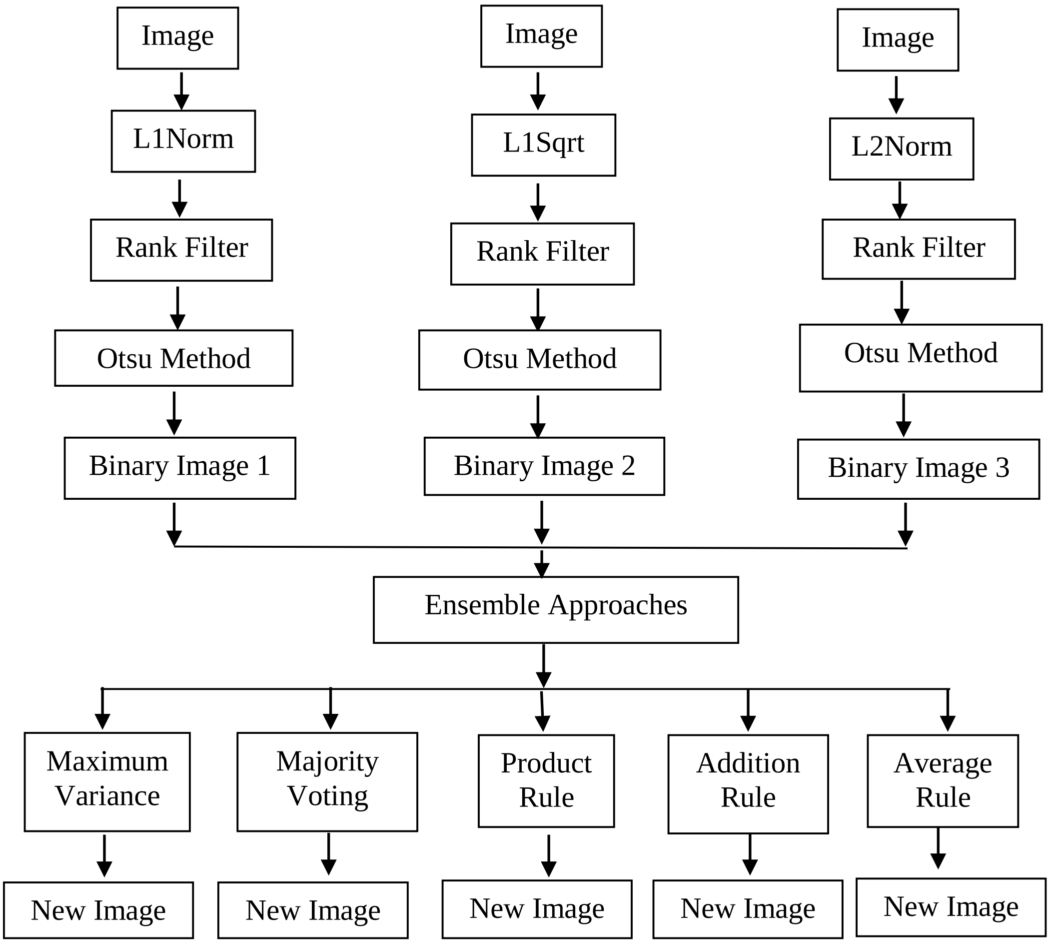

Figure 1 Flowchart of the proposed method

The DRIVE database consists of 40 eye-fundus color images which is divided into two sets i.e. test set and training set. Each set contains 20 images with diameter 768 x 584 pixels. For each set also, there are two sets of ground truth images prepared by two different experts for each image. The ground truth images prepared by the first expert will be used for evaluating algorithm performance.

The STARE database consists of 20 eye-fundus color images with diameter 700 x 605 pixels. Same as DRIVE database, there are two sets of ground truth images prepared by two different experts. Ground truth images prepared by the first expert is chosen for performance evaluation.

The DIBCO2009 database consists of 10 handwritten and printed document images while the DIBCO2011 database consists of 16 handwritten and printed document images for various diameters. Both databases have only one set of ground truth images for performance evaluation.

Experiment

For retinal images, we will select 20 images from DRIVE and STARE databases randomly and we will run the experiment for 50 runs. The combination of these two databases will be named as COMBINE_RETINA. While for document images, we will select 15 images from DIBCO2009 and DIBCO2011 databases randomly and we will also run the experiment for 50 runs. The combination of these two databases will be named as COMBINE_DOCUMENT.

The resulting image is compared to its corresponding ground truth image. The outcome of segmentation process is a pixel-based classification result. Every pixel will be classified as foreground (1) or background (0). Hence, there will be four events occurred here, true positive (*TP*), true negative (*TN*), false negative (*FN*) and false positive (*FP*). *TP* and *TN* are when a pixel is correctly classified as a foreground or background respectively, while *FN* and *FP* appears for two misclassifications. *FN* occur if a pixel is classified as background when it is not, while *FP* occur if a pixel is classified as foreground when it is a background. The performance measure used for the experiment is accuracy. The metric is defined as

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \tag{14}$$

Accuracy – global measure giving the ratio of total correctly classified pixels.

In order to determine weights for each normalization techniques, each combination of databases will be run for 50 runs and the average accuracy will be determined. The experiment had been done by using 40 images from COMBINE_RETINA and 26 images from COMBINE_DOCUMENT. Table 1 shows the results of the average accuracy with its standard deviation for normalization techniques for each combination databases.

Table 1 Accuracy Results For 50 Runs of COMBINE_RETINA and COMBINE_DOCUMENT for L1-Norm, L1-Sqrt, L2 – Norm.

Method	COMBINE_RETINA	COMBINE_DOCUMENT
	Average Accuracy	Average Accuracy
L1Norm	$\mathbf{0.9360 \pm 0.0238}$	$\mathbf{0.9452 \pm 0.0745}$
L1Sqrt	$\mathbf{0.9448 \pm 0.0170}$	$\mathbf{0.9492 \pm 0.0593}$
L2Norm	$\mathbf{0.9365 \pm 0.0227}$	$\mathbf{0.9496 \pm 0.0660}$

Based on these results, weights will be assigned for each normalization techniques. Normalization technique that produce higher average accuracy will be given higher weight while normalization technique with lower average accuracy will be given lower weight. Weights will be between 0 to 1 and $\sum_1^3 \boldsymbol{w_i} = \mathbf{1}$.

For COMBINE_RETINA: weights for L1Norm, L1Sqrt and L2Norm will be assigned as:

$w_1 = 0.2$, $w_2 = 0.5$ and $w_3 = 0.3$, respectively.

For COMBINE_DOCUMENT: weights for L1Norm, L1Sqrt and L2Norm will be assigned as:

$w_1 = 0.2$, $w_2 = 0.3$ and $w_3 = 0.5$, respectively.

Then, the experiment for the proposed methods will be run for 50 runs. Binary images which have the maximum between class variance (Maximum Variance) from the three binary images obtained by applying normalization techniques and Otsu method have been selected for the first final image. Next, we compare pixels for each location in binary images obtained and counting number of 0s or 1s at a particular location for Majority Voting for second final image.

Based on the results in Table 1, we put weights for each normalization techniques. Then, we apply Product Rule, Addition Rule and Average Rule for the weights. The results of the proposed methods are as shown in Table 2.

Table 2 Accuracy Results For 50 Runs of COMBINE_RETINA and COMBINE_DOCUMENT for the standard Otsu method and proposed methods.

Method	COMBINE_RETINA	COMBINE_DOCUMENT
	Average Accuracy	Average Accuracy
Standard Otsu Method	$\mathbf{0.9161 \pm 0.1064}$	$\mathbf{0.9488 \pm 0.0724}$
Maximum Variance	$\mathbf{0.9539 \pm 0.0125}$	$\mathbf{0.9680 \pm 0.0263}$
Majority Voting	$\mathbf{0.9533 \pm 0.0143}$	$\mathbf{0.9672 \pm 0.0263}$
Product Rule	$\mathbf{0.9533 \pm 0.0143}$	$\mathbf{0.9574 \pm 0.0533}$
Addition Rule	$\mathbf{0.9536 \pm 0.0130}$	$\mathbf{0.9716 \pm 0.0169}$
Average Rule	$\mathbf{0.9532 \pm 0.0145}$	$\mathbf{0.9717 \pm 0.0169}$

It is clearly shown from Table 2, the average accuracy of the proposed methods are all higher than the Otsu method. The method of Maximum Variance have the highest average accuracy and the lowest standard deviation of accuracy for COMBINE_RETINA databases while for COMBINE_DOCUMENT, the method of Average Rule have the highest average accuracy and the lowest standard deviation of accuracy. The normality of the data are checked whether they are appropriate to perform significance test to compare the average accuracy between the standard Otsu method and the proposed methods by applying Kolmogorov-Smirnov normality test. It is found that the data are all normally distributed and suitable for parametric hypothesis testing. Then, the significance test is done by applying hypothesis testing between two populations to compare the average accuracy between the standard Otsu method with the proposed methods.

From the significance test of COMBINE_RETINA dataset, it is found that all average accuracy of the proposed methods i.e. Maximum Variance, Majority Voting, Product Rule, Addition Rule and Average Rule are significantly higher than the standard Otsu method at 0.05 significance level with p-values are all 0. For COMBINE_DOCUMENT, the p-values for significance test for proposed methods i.e. Maximum Variance, Majority Voting, Product Rule, Addition Rule and Average Rule are 6.7552e-012, 4.4903e-011, 5.5511e-017.0.0043 and 5.5511e-017 respectively. From Table 2, all standard deviation of the proposed methods are lower than Otsu method which implies that the proposed method is robust. Figure 2 show the images obtained by using the standard Otsu method and Maximum Variance method for COMBINE_RETINA. Figure 3 show the images obtained by using the Otsu method and Average Rule method for COMBINE_DOCUMENT. It can be seen in Figure 2, the retina blood vessels obtained in (b) have less noise compared to (a). While in Figure 3, the hand writing are clearer and less noise in the right hand side part in (b) compared to by using the standard Otsu method in (a).

(a) (b)

Figure 2 Image obtained from (a) Otsu Method (b) Maximum Variance

(a) (b)

Figure 3 Image obtained from (a) Otsu Method (b) Average Rule

6 Discussion and Conclusion

The above results show that normalization techniques and their ensembles affect the performance of Otsu method. All ensembles of normalization techniques that have been proposed are significantly had higher average accuracy compared to standard

Otsu method for retinal images in DRIVE and STARE databases. The same results also obtained for document images in DIBCO2009 and DIBCO2011 databases. Otsu method have used between-class variance as a discriminant criterion in order to maximize the separation between classes. Since calculation of variance using gray level values, variance is very sensitive towards the changes of gray level values. Hence, we apply normalization techniques where the calculation of variance values will be affected and gray level values will be transformed into zero to one. By applying normalization techniques, have make the range of feature space for gray level values became smaller and this also had eliminated the domination of certain values. Thus, the problem of biasness will be reduced and hence, it can improve Otsu method.

Nonlinear filters have the robustness properties towards noise. So, rank filtering have been applied to eliminate noises and to preserve edge information. Systems that based on ensemble approaches have shown to produce better results compared to those of single-expert systems in a broad range of applications and under a variety of scenarios. Hence, by using ensemble approaches, the strength and the weaknesses of each normalization techniques can be maintained.

All ensemble methods i.e. Maximum Variance, Majority Voting, Product Rule, Addition Rule and Average Rule, used in this experiment have produces significant results compared to standard Otsu method. However, the weights applied for each normalization technique have not yet been optimized. Some improvements to the proposed methods are still needed. Ways of optimizing weights for each normalization techniques are necessary and our future work will look into their effect on Otsu method.

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