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# WEIGHT DETERMINATION FOR SUPERVISED BINARIZATION ALGORITHM BASED ON QR DECOMPOSITION

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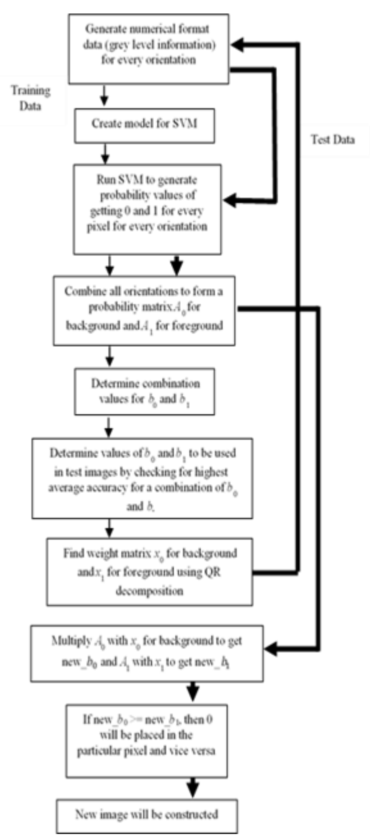
## Graphical abstract




## Abstract

Supervised binarization is a method that learn pre-classified data in order to classify a particular pixel whether it is belong to a foreground or a background. The performance of supervised approach is usually better than that of unsupervised ones since it is designed to use classification criteria determined by ground truth data. By using this approach, orientations of local neighbourhood grey level information that are based on eight orientations have been developed to characterize a particular pixel. These orientations are combined together since it may reduce the risk of making a particular poor selection of these orientations. In order to ensemble all orientations, heuristic method have been used to determine weights for each orientation. However, determination of weights using heuristic method is not efficient and not enough as it provides incomplete information. Furthermore, these orientations might be influenced by other different factors. This will lead to wrongly assigning weights to a particular orientation. Hence, determination of weights to combine eight orientations to characterize a particular pixel by using QR decomposition method is proposed. By using QR decomposition method, computational complexity is low and weights obtained for each orientation are optimal. In order to test the proposed approach, 21 document images from DIBCO2009 and DIBCO2011 databases and 55 retinal images from DRIVE and STARE databases have been used. The results of the proposed method clearly show significant improvement where higher average accuracy is obtained compared to by using heuristic method.

*Keywords:* Binarization, local neighbourhood, ensemble, weights, QR decomposition method

## Abstrak

Pembinarian terselia adalah satu kaedah yang mempelajari data pra pengelasan untuk mengelaskan sesuatu piksel sama ada ianya dipunyai oleh latar hadapan atau latar belakang. Prestasi bagi pendekatan terselia adalah selalunya lebih baik berbanding dengan pendekatan tidak terselia kerana ia direkabentuk untuk menggunakan kriteria pengelasan yang ditentukan oleh data yang sedia ada. Dengan menggunakan pendekatan ini, orientasi bagi kejiranan tempatan maklumat aras kelabu yang berdasarkan lapan orientasi telah dibina untuk mencirikan sesuatu piksel. Orientasi ini kemudiannya digabungkan bersama kerana ianya boleh mengurangkan risiko pemilihan orientasi yang salah. Untuk menggabungkan kesemua orientasi ini, kaedah heuristik telah digunakan untuk menentukan pemberat bagi setiap orientasi. Walau bagaimanapun penentuan pemberat menggunakan kaedah heuristik adalah tidak efisien dan tidak mencukupi kerana ia tidak memberikan maklumat yang lengkap. Lagipun orientasi ini mungkin dipengaruhi oleh pelbagai faktor yang berbeza-beza. Ini akan menyebabkan nilai pemberat yang salah diberikan kepada sesuatu orientasi. Oleh itu penentuan pemberat bagi penggabungan lapan orientasi untuk mencirikan sesuatu piksel dengan menggunakan kaedah dekomposisi QR telah dicadangkan. Dengan menggunakan kaedah dekomposisi QR, kekompleksan pengiraan adalah rendah dan pemberat yang diperolehi bagi setiap orientasi adalah optimum. Untuk menguji pendekatan yang dicadangkan, 21 imej dokumen daripada pangkalan data DIBCO2009 dan DIBCO2011 dan 55 imej retina daripada pangkalan data DRIVE dan STARE telah digunakan. Keputusan daripada kaedah yang dicadangkan telah menunjukkan dengan jelas peningkatan yang signifikan iaitu purata ketepatan yang lebih tinggi telah diperolehi berbanding dengan menggunakan kaedah heuristik.

*Kata kunci:* Pembinarian, kejiranan tempatan, penggabungan, pemberat, kaedah dekomposisi *QR*



## 1.0 INTRODUCTION

Binarization is known as one of the most important steps in high-level image analysis systems, specifically for recognition of object. Some of the applications in binarization are in segmenting medical images [1], document image analysis [2], human detection [3], detecting pupil location [4], automated visual inspection of defects [5] and many more. Binarization is crucial to remove unrelated information, noise, background noise or variation in contrast and illumination [6]. Hence, binarization process is very important because a good binarization will result in better recognition accuracy for any pattern recognition application [6]. If these steps are inefficient, the important parts in the image will be lost or more noise will be added [7].

One of ways to do binarization is by using supervised approach. The binarization process will be put as a two class classification process for a particular pixel. Some prior labelling information is needed to decide whether a pixel belongs to foreground or background. The algorithm will learn the rule for binarization based on training the available ground truth images. In order to characterize a particular pixel for binarization, a set of grey level values can be used. Some low level features like lines, edges, corners and junctions appear in images in arbitrary orientations [8]. Furthermore, noise can be removed and oriented structures can be enhanced if oriented filtering is done [9]. Due to these advantages, eight orientations [10] which are 0 degree, 45, 90, 135, 180, 225, 270 and 315 degrees that contain set of feature vectors of local neighbourhood normalized intensities of grey level information of each pixel have been used to characterize a particular pixel. However, if only one best single orientation is used to describe a particular pixel, some of the low level features cannot be detected. Hence, all eight orientations will be combined in order to increase the accuracy of the classification.

Ensemble of operators are very beneficial for using available information in a best way. Weighted average is one of the most common ensemble of operators where the information will be ensembled by assigning distinct degrees of importance to the information [11]. Distinct degrees of importance are very essential as some information are more important than others [12]. In order to determine weight for each information, heuristic method have been used in which if a certain information give higher accuracy, then higher weight will be given to that particular information. Otherwise, it will be given lower weight. However, information is very complicated and always influenced by different factors of ambiguities in real world problems [11]. Thus, the use of heuristic methods to determine weights for a particular information is not enough as it provides incomplete information and sometimes this may lead to wrong decisions. In order to get weights for each orientation, QR decomposition method can be used to linearly combine these eight orientations and hence matrix of weights for the orientations can be determined. QR decomposition method have been chosen to determine weights because this method is fast and have low computational complexity [13]. Furthermore, QR decomposition method enjoys numerical stability [14].

There are various methods in the literature that can determine weights for various application. Researchers in [15] determined the optimal initial weight for feedforward neural networks using Cauchy's inequality and QR decomposition method. The algorithm is computationally efficient and increase the rate of convergence. In [16], weights were assigned adaptively for directional weighted median filters. They estimated the noise density first and then adaptively used weighted grey level mean to restore current noise pixel. Their method have significantly improved the capability of noise suppression and image detail preservation. An image spatial clustering method was carried out by [17] for image segmentation. They incorporated edge and local information in their method by introducing the weights of pixels within local neighbour windows. They have set different weights to all pixels in the image and hence were able to reduce the edges degradation. The literatures previously described have shown that determination of weights are important since different weight can result different decisions.

QR decomposition method have been used in many applications. Some of them are as in [18]. QR decomposition method have been used in image enhancement for through wall imaging (TWI). This method is capable to discriminate target, noise and clutter signals. It is found that by using QR decomposition method, their algorithm are less computational complex compared to existing singular value decomposition. Furthermore image quality is improved because clutters and noise are reduced and target signals are enhanced. Aqil *et al.* [19] have proposed an online framework for an effective real-time brain imaging application. Brain activity parameters have been estimated by assigning them with coefficients of a linear model by QR decomposition of normalized regressor functions. The method is recursive and computationally efficient for a large number of measuring channels and the method is applicable for real-time brain imaging. Another application of QR decomposition was proposed in [20]. They presented a new algorithm for background subtraction. In their algorithm, background was identified based on QR decomposition method where R-values were applied to decompose a given system. From R-values, the background blocks with the weakest contribution can be selected. The experimental results show a better performance with respect to some other methods. A blind watermarking technique in still images based on QR decomposition has been proposed by [13]. The method is implemented in wavelet domain and the R matrix obtained from QR decomposition is used to embed the watermark. The method are robust compared to other image processing techniques such as rotation, median filtering, average filtering and salt and pepper noise. Researchers in [13] have claimed that one of the important advantages of using QR decomposition is, it has low computational complexity. Due to the advantages of the previous works outlined above, we have proposed an efficient weight determination for the ensemble of single oriented local neighbourhood grey level information (ESOLNGLI) by using QR decomposition method.

The rest of the paper is organized as follows: Section 2 reviews the related works. Section 3 and 4 describe theoretical background of the proposed method. The experimental results are shown in Section 5. Section 6 discusses and concludes this paper.

# 2.0 METHODOLOGY

## 2.1 Fundamentals of QR Decomposition Method

We first describe the fundamental principle of the methods used in the experiment.

In order to use QR decomposition (described in detail in [21]), consider solving the linear equations system

$$Ax = b \tag{1}$$

where $A$ is an $m*n$ matrix, $x$ is an $n*k$ column vector and $b$ is an $m*k$ column vector. When $m > n$, then this will lead to an overdetermined system which in general has no solution [21]. For minimization problem, in order to minimize the residual

$$r = b - Ax \tag{2}$$

Hence we obtain the linear least squares problem (LSP) that is given

$$A \in \Re^{m\times n}, m \geq n, b \in \Re^{m}, \text{find } x \in \Re^{m} \text{ such that}$$

$$\|b - Ax\|_2 \text{ is minimized.} \tag{3}$$

$x$ is the solution to the normal equations

$$A^T Ax = A^T b \tag{4}$$

Geometrically, we are trying to get the point $x$ in range ($A$) that is the closest to $b$ as in Figure 1.

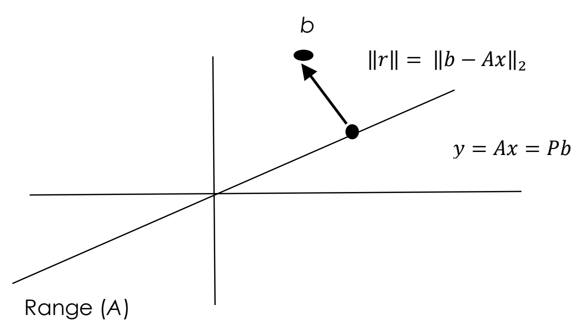



**Figure 1** Graphical representation of Least Squares Solution

$$Ax = Pb \tag{5}$$

where $P$ is an orthogonal projector onto range ($A$). So the residuals must be orthogonal to range ($A$). The LSP can be solved by using QR decomposition by using

$$A = QR \tag{6}$$

$b$ can be projected onto range (A) by $P = QQ^T$. $Q$ is an orthogonal matrix $Q \in \Re^{m \times m}$ and $R$ is upper triangular matrix, $R \in \Re^{m \times n}$.

By substituting (6) into (5),

$$QRx = QQ^T b$$
$$(QR)^T (QR)x = (QR)^T b$$
$$R^T Q^T Rx = R^T Q^T b$$

and $Q^T Q = I$, then

$$R^T Rx = R^T Q^T b$$

Hence

$$Rx = Q^T b \quad \text{where } R \text{ is nonsingular matrix} \qquad (7)$$

and $\|r\| = \|Rx - Q^T b\|$. $x$ is solved by using backward substitution method.

## 2.2 Ensemble of Single Oriented Local Neighbourhood Grey Level Information Using QR Decomposition Method (ESOLNGLI_QR)

In supervised approaches, some prior labelling information is used to decide whether a particular pixel belongs to foreground or background. Available ground truth images will be used to give the correct label for a set of features that is being used to describe a pixel during training session. Feature extraction plays an important role in the description of a pixel because its distinctive features can determine the results of the binarization process no matter how well the design of the method used or experiment done [22]. In this work, a set of normalized intensities of grey level values have been used to represent a particular pixel. Support Vector Machine (SVM) have used this set of features to classify a target pixel, ***P***, either as a foreground (1) or background (0) where this target pixel is the particular pixel to be described. Eight single oriented local neighbourhoods of grey level information (SOLNGLI) have been developed. The orientations are 0, 45, 90, 135, 180, 225, 270, 315 degrees and are shown in Figure 2. These orientations are used in order to identify some small objects like edges, junctions, lines and corners since these small objects can be better detected in various orientations [8]. The 3 X 3 neighbourhood pixels used for each orientations are shown in Figure 3. Point, ***R***, will be used as a reference pixel for a particular orientation. The small size of the neighbourhood pixels are used in this work because to achieve high de-noising with low complexity [23].

LIBSVM is a library support for Support Vector Machine [24] and it is used to perform classification in this work. Pixel values of a neighbourhood of 3 X 3 window is chosen as the features for each target pixel. The value of labels for foreground (1) and background (0) for each target pixel will be given by ground truth images and these labels are followed by their neighbour values.

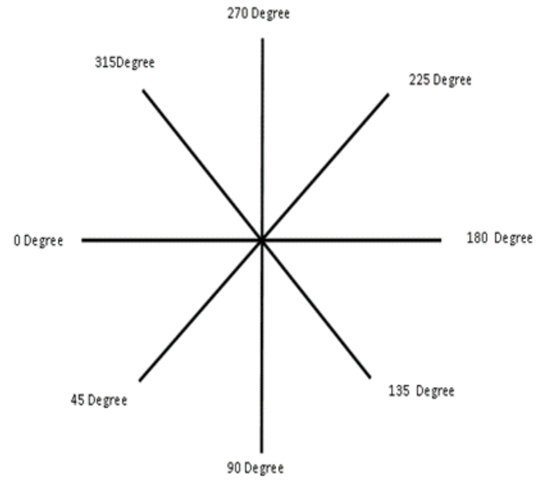



**Figure 2** Eight orientations to describe a target pixel

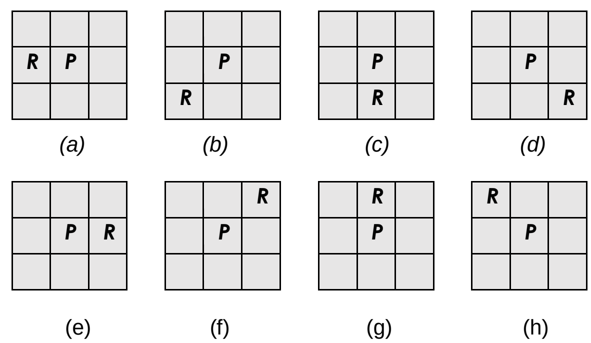



**Figure 3** Single oriented local neighbourhood grey level information (SOLNGLI) for 8 orientations. (a) 0 degree (b) 45 degrees (c) 90 degrees (d) 135 degrees (e) 180 degrees (f) 225 degrees (g) 270 degrees (h) 315 degrees. ***P*** is the target pixel and ***R*** is the reference pixel based on orientation

Five randomly images have been selected and used as training images and hence a model is constructed. SVM have used this model SVM to classify test images. The results of SVM classifier are in the form of probability where the probability of label 0 and label 1 have been given to each pixel. In order to ensemble the orientations, QR decomposition method have been used and the weight have been produced for each orientation. Hence, ensemble of single oriented local neighbourhood grey level information using QR decomposition method (ESOLNGLI-QR) is proposed. From training images, for each background (0) and foreground (1), let $A_o$ and $A_1$ be the probability matrix of each orientation respectively.

For background:

$$A_0 = [Prob0_1; Prob0_2; Prob0_3; Prob0_4; Prob0_5; Prob0_6; Prob0_7; Prob0_8] \quad (8)$$

For foreground:

$$A_1 = [Prob1_1; Prob1_2; Prob1_3; Prob1_4; Prob1_5; Prob1_6; Prob1_7; Prob1_8] \quad (9)$$

where subscript 1, 2, 3, 4, 5, 6, 7 and 8 represent 0, 45, 90, 135, 180, 225, 270 and 315 degrees respectively. $A_0$ and $A_1$ are $m \times n$ matrix where $m$ = number of pixels involved and $n$ = 8 orientations.

For each background and foreground, the following linear system is used.

$$A_0 x_0 = b_0 \quad (10)$$

and

$$A_1 x_1 = b_1 \quad (11)$$

Matrix $x_0$ and $x_1$ are the $n \times 1$ matrix of weights for each orientation to be determined by using QR decomposition method. The value of $b_0$ and $b_1$ have been determined from the experiment of training images. A combination of values that achieve highest average accuracy from training images will be selected for the values of $b_0$ and $b_1$. The experiment have been run for training images to find values of $b_0$ and $b_1$ ranging from 0 to 20 with a step of 0.5 to get the best average accuracy. Negative values and values of more than 20 cannot be used for $b_0$ and $b_1$ since the results obtained are not good. The values which gave the best average accuracy performance are picked and used on the test images.

Both linear equation systems for background and foreground have been solved using QR decomposition method to get the matrix weight $x_0$ and $x_1$. Then this matrix weight $x_0$ and $x_1$ are multiplied back with $A_0$ and $A_1$ respectively. For each pixel, if the new value of

$$new\_b_0 > new\_b_1 \quad (12)$$

then zero (0) is placed in that particular location and vice versa. The flowchart of the proposed method is shown in Figure 4.

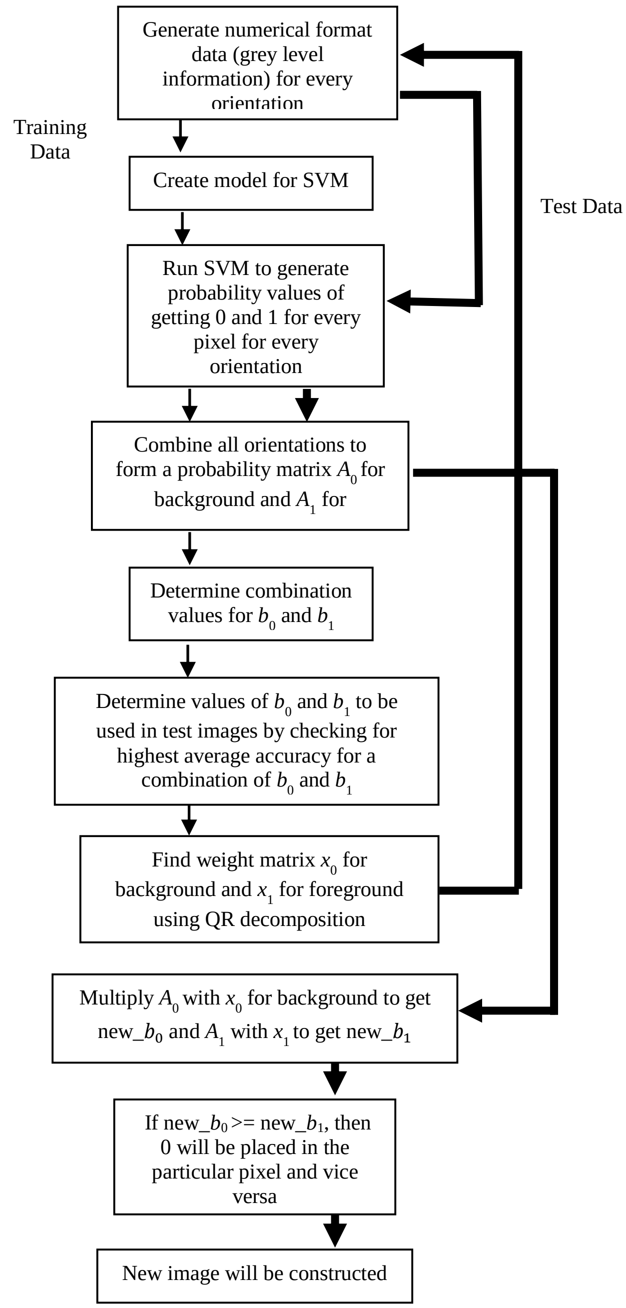



**Figure 4** The steps of the proposed method

## 3.0 RESULTS AND DISCUSSION

Two types of publicly available databases i.e. document images and retinal images are used to evaluate the proposed method. Databases from DIBCO2009 [25] and DIBCO2011 [26] for document images and databases from DRIVE [27] and STARE [28] for retinal images are used in the experiment. DIBCO2009 and DIBCO2011 databases are used to evaluate document binarization while DRIVE and STARE databases are used to evaluate the blood vessel segmentation.

These databases are chosen because they have been used by other researchers widely and most importantly, these databases provide manual segmentation for performance evaluation. There are 26 document images in DIBCO2009 and DIBCO2011 and five of them are chosen randomly as training images. DRIVE and STARE databases consists of 60 retinal images and five of them also are selected randomly for training images.

In order to evaluate the proposed method, 10 document images are selected randomly from the combination of DIBCO2009 and DIBCO2011 databases and their combination are named as DOCUMENT_DATA. For retinal images, 20 images are selected randomly from DRIVE and STARE databases and their combination are named as RETINA_DATA. The five images used for training are excluded from testing the accuracy of the classifier. The experiment consists of 100 runs for each of the combined databases. The resulting images is compared to its corresponding ground truth images.

The outcome of this supervised binarization process is a pixel-based classification result. Every pixel is either classified as foreground (1) or background (0) pixels. Hence, there will be four possible outcomes that can occur, true positive (*TP*), true negative (*TN*), a false negative (*FN*) and a false positive (*FP*). *TP* and *TN* are when a pixel is correctly classified as a foreground or background respectively, while *FN* and *FP* are 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 actually a background. The performance measure used for the experiment is Accuracy. The metric is defined as in equation (13).

$$Accuracy = (TP + TN)/(TP + FN + TN + FP) \qquad (13)$$

Another quality measurement of segmentation result used is misclassification error (ME) [29] measure that regards image segmentation as a pixel classification process. It reflects the percentage of background pixels incorrectly classified into foreground and conversely foreground pixels erroneously assigned to background. ME is formulated as in equation (14).

$$ME = 1 - \frac{|B_o \cap B_T| + |F_o \cap F_T|}{|B_o| + |F_o|} \qquad (14)$$

where $B_o$ and $F_o$ are the background and foreground of the ground truth image, $B_T$ and $F_T$ the background and foreground pixels in the segmented image, and | . | is a cardinality of a set. A lower value of ME means better quality of segmented image and it range from 0 to 1. Another measure used for evaluation is root mean square error (RMSE). RMSE is given by the equation 15.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^{2}} \qquad (15)$$

where e is the error between ground truth image and segmented image. A lower value of RMSE means a better quality of segmented image.

The experiment is run by using the proposed method and have been compared with Addition Without Weight method and Addition With Weight Heuristically method where the weight have been determined heuristically. Addition Without Weight method is the method where for each background and foreground, the probabilities are added without consideration of weights. This can be expressed by the following.

For background (0): $\sum_{k=1}^{8} \mathrm{Prob}_{0k}$ (16)

For foreground (1): $\sum_{k=1}^{8} \mathrm{Prob}_{1k}$ (17)

Addition With Weight Heuristically method is the method where the weight is determined by running the training images. All single oriented local neighbourhood grey level information is combined using ensemble approaches as in [30]. If the average accuracy obtained for a particular orientation is higher, then it is given higher weight. Otherwise, it is given lower weight. This can be represented by the following.

For background (0): $\sum_{k=1}^{8} w_{0k}\,\mathrm{Prob}_{0k}$ (18)

For foreground (1): $\sum_{k=1}^{8} w_{1k}\,\mathrm{Prob}_{1k}$ (19)

For document images, since most parts in document images are foreground (1), then higher weight also is given to foreground (1). While for retinal images, most parts are background (0), then higher weight also is assigned to background (0). Weights for each orientation for both databases have been assigned as:

For DOCUMENT_DATA: weights for each orientation have been assigned as:

Background (0): $w_{0k} = 1/k$ (20)

Foreground (1): $w_{1k} = 2/k$ (21)

For RETINA_DATA: weights for each orientation have been assigned as:

Background (0): $w_{0k} = 2/k$ (22)

Foreground (1): $w_{1k} = 1/k$ (23)

where *k* is the ranking for eight single orientations that are based on average accuracy results in training images. The results for each orientation are as shown in Table 1. The proposed method also have been compared with existing binarization methods. They are Minimum Error [31], Otsu [32] and Niblack [33] methods. The experiment for all methods that are to compare with the proposed method are also run for 100 runs and the results obtained are as in Table 2.

From Table 1, it can be seen that most of the SOLNGLI have lower average accuracy compared to by ensemble all these SOLNGLI as in Table 2. These results show that by using ensemble approach, average accuracy of the binarization can be improved. Based on Table 2, the proposed method, ESOLNGLI-QR have the highest average accuracy compared to Addition Without Weight, Addition With Weight Heuristically, Minimum Error [31], Otsu [32] and Niblack [33] methods for both types of images. The weight obtained by using QR decomposition method is optimal and able to eliminate noises in the resultant images. From its standard deviation, it can be seen that, ESOLNGLI-QR method is more stable and robust since its standard deviation is the lowest compared with other methods. Significance tests are also performed to check whether the average accuracy for the ESOLNGLI-QR method are significantly higher than Addition Without Weight and Addition With Weight Heuristically method.

**Table 1** Average and its standard deviation for accuracy results for each orientation. DOCUMENT_DATA - database for document images and RETINA_DATA – database for retinal images

| Orientation | DOCUMENT_DATA | RETINA_DATA |
|---|---|---|
| | **Average Accuracy** | **Average Accuracy** |
| 0 degree | $0.9622 \pm 0.0220$ | $0.9004 \pm 0.0306$ |
| 45 degree | $0.9557 \pm 0.0300$ | $0.9141 \pm 0.0219$ |
| 90 degree | $0.9531 \pm 0.0322$ | $0.9101 \pm 0.0224$ |
| 135 degree | $0.9512 \pm 0.0361$ | $0.9138 \pm 0.0232$ |
| 180 degree | $0.9567 \pm 0.0279$ | $0.9228 \pm 0.0190$ |
| 225 degree | $0.9541 \pm 0.0324$ | $0.9100 \pm 0.0235$ |
| 270 degree | $0.9587 \pm 0.0276$ | $0.9126 \pm 0.0233$ |
| 315 degree | $0.9514 \pm 0.0314$ | $0.9141 \pm 0.0211$ |

**Table 2** Average and its standard deviation for accuracy, misclassification error (ME) and root mean square error (RMSE) results for Addition Without Weight, Addition With Weight Heuristically, ESONGLI-QR method (proposed method), Minimum Error, Otsu and Niblack methods. DOCUMENT_DATA - database for document images and RETINA_DATA – database for retinal images

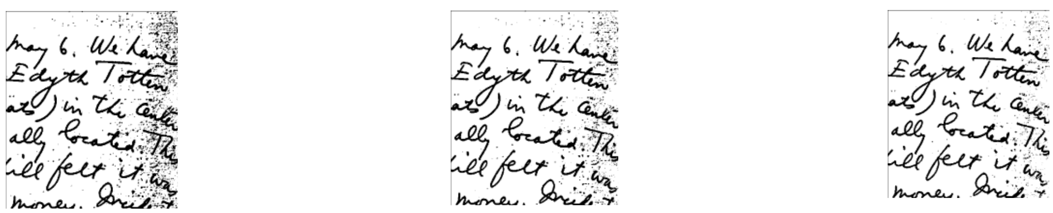
| Method | DOCUMENT_DATA | | | RETINA_DATA | | |
|---|---|---|---|---|---|---|
| | **Average Accuracy** | **Average ME** | **Average RMSE** | **Average Accuracy** | **Average ME** | **Average RMSE** |
| Addition Without Weight | $0.9602 \pm 0.0257$ | $0.0398 \pm 0.0257$ | $0.1888 \pm 0.0646$ | $0.9173 \pm 0.0211$ | $0.0827 \pm 0.0211$ | $0.2851 \pm 0.0368$ |
| Addition With Weight Heuristically | $0.9710 \pm 0.0171$ | $0.0290 \pm 0.0171$ | $0.1624 \pm 0.0509$ | $0.9311 \pm 0.0128$ | $0.0689 \pm 0.0128$ | $0.2614 \pm 0.0245$ |
| ESOLNGLI-QR - Proposed Method | $\mathbf{0.9747 \pm 0.0155}$ | $\mathbf{0.0253 \pm 0.0155}$ | $\mathbf{0.1524 \pm 0.0458}$ | $\mathbf{0.9376 \pm 0.0098}$ | $\mathbf{0.0624 \pm 0.0098}$ | $\mathbf{0.2490 \pm 0.0195}$ |
| Minimum Error [31] | $0.9374 \pm 0.0603$ | $0.0626 \pm 0.0603$ | $0.2235 \pm 0.1124$ | $0.4325 \pm 0.0449$ | $0.5675 \pm 0.0449$ | $0.7526 \pm 0.0342$ |
| Otsu [32] | $0.9627 \pm 0.0424$ | $0.0373 \pm 0.0424$ | $0.1718 \pm 0.0885$ | $0.8821 \pm 0.0368$ | $0.1179 \pm 0.0368$ | $0.3401 \pm 0.0475$ |
| Niblack [33] | $0.9427 \pm 0.0303$ | $0.0573 \pm 0.0303$ | $0.2309 \pm 0.0633$ | $0.8354 \pm 0.0234$ | $0.1649 \pm 0.0234$ | $0.4047 \pm 0.0298$ |

From the significance test for DOCUMENT_DATA and RETINA_DATA, it is found that average accuracy of the proposed methods is significantly higher than Addition Without Weight and Addition With Weight Heuristically at 0.05 significance level with p-values are both 0 respectively. Hence, for document images and retinal images, the method of determining of weights using QR decomposition have significantly higher average accuracy than Addition Without Weight and Addition With Weight Heuristically method.

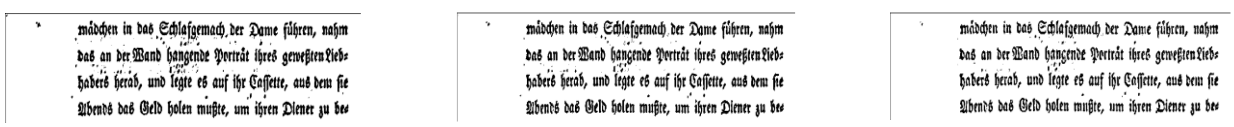
Figure 5 show some sample images from DIBCO2009 and DIBCO2011 database that are processed by using Addition Without Weight, Addition With Weight Heuristically and the proposed method. From Figure 5, it can be seen that the noise are reduced and the writings are clearer for the proposed method. Figure 6 show some sample images from DRIVE and STARE database that are processed by using Addition Without Weight, Addition With Weight Heuristically and ESOLNGLI-QR method. For the proposed method in Figure 6, the noise are suppressed, the blood vessels are solid and false blood vessels have been reduced.

## 4.0 CONCLUSION

The results from the experiment show that the addition method that use weights determined from QR decomposition method outperforms the addition method that do not use any weight and also it outperforms the addition with weight method that used weights that have been determined heuristically from training images. This is due to the fact weights that have been determined heuristically are not stable and may not be accurate if the weights assigned are inappropriate. Furthermore, each orientation might be affected by many factors that can lead to wrong weights assigned for each orientation.

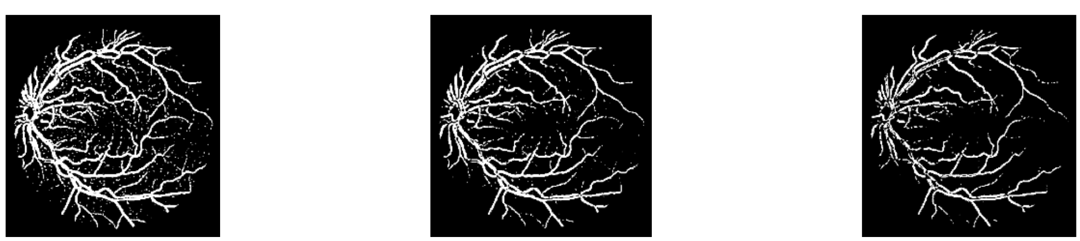


(a) (b) (c)

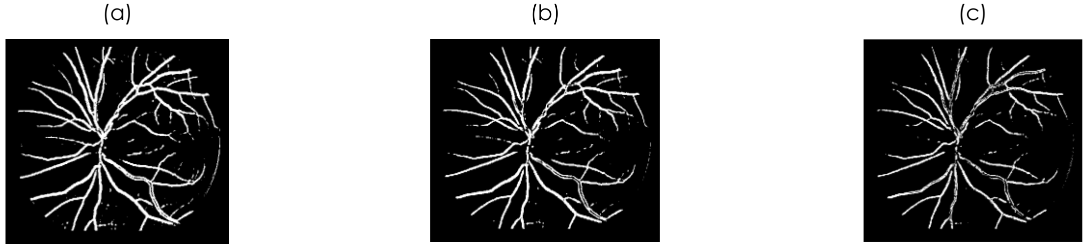


(a) (b) (c)

**Figure 5** Image obtained from (a) Addition Without Weight (b) Addition With Weight Heuristically (c) ESOLNGLI-QR (Proposed Method) for DIBCO2009 and DIBCO2011 database



(a) (b) (c)



(a) (b) (c)

**Figure 6** Image obtained from (a) Addition Without Weight (b) Addition With Weight Heuristically (c) ESOLNGLI-QR (Proposed Method) for DRIVE and STARE database

The reason of using QR decomposition to determine weights is because QR decomposition method is fast, low computational complexity and the weights obtained are optimal. By using QR decomposition, binarization of images become more accurate and it helps in binarization and segmentation of document images [34], segmentation of medical images [35], detecting defects in visual inspection for machine vision industry [5] and airplane extraction using high resolution satellite images [36]. However, in order to use QR decomposition method, we need to assume that all orientations are linearly related. But this is not always true for all cases. Further research need to be done to find how the orientations are related to each other.

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## References

[1] LaTorre, A., Alonso-Nanclares, L., Muelas, S., Peña, J. M. and DeFelipe, J. 2013. Segmentation Of Neuronal Nuclei Based On Clump Splitting And A Two-Step Binarization Of Images. *Expert Syst. Appl.* 40(16): 6521-6530.

[2] Ahmadi, E., Azimifar, Z., Shams, M., Famouri, M., and Shafiee, M., J. 2015. Document Image Binarization Using A Discriminative Structural Classifier. *Pattern Recognit. Lett.* 63: 36-42.

[3] Xie, S., Li, Y., Jia, Z., and Ju, L. 2013. Binarization Based Implementation For Real-Time Human Detection. *23rd Int. Conf. F. Program. Log. Appl*. 1-4.

[4] Lin, Z., and Yu, H. 2011. The Pupil Location Based on the OTSU Method and Hough Transform. *Procedia Environ. Sci.* 8: 352-356.

[5] Ng, H., F. 2006. Automatic Thresholding For Defect Detection. *Pattern Recognit. Lett.* 27(14): 1644-1649.

[6] Chaki, N., Shaikh, S., H., and Saeed, K. 2014. A Comprehensive Survey on Image Binarization Techniques. *Explor. Image Bin. Tech. Stud. Comput. Intell.* 560: 5-16.

[7] Chamchong, R. 2010. A Review of Evaluation of Optimal Binarization Technique for Character Segmentation in Historical Manuscripts. *2010 Third Int. Conf. Knowl. Discov. Data Min*. 236-240.

[8] Muhlich, M., Friedrich, D., and Aach, T. 2012. Design and Implementation of Multisteerable Matched Filters. *IEEE Trans. Pattern Anal. Mach. Intell.* 34(2): 279-291.

[9] Wilson, R., Knutsson, H., and Granlund, G. 1983. Anisotropic Nonstationary Image Estimation and Its Applications: Part II--Predictive Image Coding. *IEEE Trans. Commun.* 31(3): 388-397.

[10] Ha, J., C. 2011. *Real-Time Visual Tracking Using Image Processing and Filtering Methods*. Proquest Umi Dissertation Publishing.

[11] Merigó, J., M., Casanovas, M., and Yang, J., B. 2014. Group Decision Making With Expertons And Uncertain Generalized Probabilistic Weighted Aggregation Operators. *Eur. J. Oper. Res.* 235: 215-224.

[12] Bin Yan, H., Huynh, V., N., Nakamori, Y., and Murai, T. 2011. On Prioritized Weighted Aggregation In Multi-Criteria Decision Making. *Expert Syst. Appl.* 38(1): 812-823.

[13] Naderahmadian, Y., and Hosseini-Khayat, S. 2010. Fast Watermarking Based On QR Decomposition In Wavelet Domain. *Proc. - 2010 6th Int. Conf. Intell. Inf. Hiding Multimed. Signal Process. IIHMSP 2010*. 127-130.

[14] Zhou, S., and Shi, J. 2004. Identification Of Non-Linear Effects In Rotor Systems Using Recursive QR Factorization Method. *J. Sound Vib.* 270(1-2): 455-469.

[15] Yam, J., Y., F., and Chow, T., W., S. 2000. A Weight Initialization Method For Improving Training Speed In Feedforward Neural Network. *Neurocomputing*. 30: 219-232.

[16] Li, Z., Liu, G., Xu, Y., and Cheng, Y. 2014. Modified Directional Weighted Filter For Removal Of Salt & Pepper Noise. *Pattern Recognit. Lett.* 40: 113-120.

[17] Li, N., Huo, H., Zhao, Y., M., Chen, X., and Fang, T. 2013. A Spatial Clustering Method With Edge Weighting For Image Segmentation. *IEEE Geosci. Remote Sens. Lett.* 10(5): 1124-1128.

[18] Riaz, M., M., and Ghafoor, A. 2012. QR Decomposition based Image Enhancement for Through Wall Imaging. *IEEE Conference Proceedings*. 978-983.

[19] Aqil, M., Hong, K., Jeong, M., Y., and Ge, S., S. 2012. Online Brain Imaging by QR Factorization of Normalized Regressor Functions. *Proceedings of 2012 IEEE International Conference on Machatronics and Automation*. 1370-1374.

[20] Amintoosi, M., Farzam, F., Fathy, M., Analoui, M., and Mozayani, N. 2007. QR Decomposition-Based Algorithm for Background Subtraction. *IEEE Conference Proceedings*. 1093-1096.

[21] Golub, G., H., and Van Loan, C., F. 1996. *Matrix Computations*. The John Hopkins University Press.

[22] Tuntas, R. 2014. The Modelling And Analysis Of Nonlinear Systems Using A New Expert System Approach. *Iran. J. Sci. Technol. A*. 3: 365-372.

[23] Ibrahim R., W., and Jalab, H., A. 2015. Image Denoising Based On Approximate Solution Of Fractional Cauchy-Euler Equation By Using Complex-Step Method. *Iran. J. Sci. Technol. A*. 243-251.

[24] Hsu, C., Chang, C., and Lin, C. 2010. *A Practical Guide to Support Vector Classification.*

[25] Gatos, B., Ntirogiannis, K., and Pratikakis, I. 2009. ICDAR 2009 Document Image Binarization Contest (DIBCO 2009). *10th International Conference on Document Analysis and Recognition*. 1375-1382.

[26] Pratikakis, I., Gatos, B., and Ntirogiannis, K. 2011. ICDAR 2011 Document Image Binarization Contest (DIBCO 2011). *International Conference on Document Analysis and Recognition*. 1506-1510.

[27] Staal, J., Abràmoff, M. D., Niemeijer, M., Viergever,M., A., and Van Ginneken, B. 2004. Ridge-based Vessel Segmentation in Color Images of the Retina. *IEEE Trans. Med. Imaging*. 23(4): 501-509.

[28] Hoover, A., Kouznetsova, V. and Goldbaum, M. 2000. Locating Blood Vessels In Retinal Images By Piecewise Threshold Probing Of A Matched Filter Response. *IEEE Trans. Med. Imaging*. 19(3): 203-10.

[29] Yasnoff, W., A., Mui, J., K., and Bacus, J., W. 1977. Error Measures For Scene Segmentation. *Pattern Recognit.* 9(4): 217-231.

[30] Polikar, R. 2006. Ensemble Based Systems in Decison Making. *IEEE Circuits Syst. Mag.* 21-45.

[31] Kittler, J., and Illingworth, J. 1986. Minimum Error Thresholding. *Pattern Recognit.* 19(1): 41-47.

[32] Otsu, N. 1979. A Threshold Selection Method from Gray-Level Histograms. *IEEE Trans. Syst. Man, Cybern.* SMC-9(1): 62-66.

[33] Niblack, W. 1985. *An Introduction to Digital Image Processing.* Strandberg Publishing Company.

[34] Cheriet, M., Farrahi Moghaddam, R., and Hedjam, R. 2013. A Learning Framework For The Optimization And Automation Of Document Binarization Methods. *Comput. Vis. Image Underst.* 117(3): 269-280.

[35] Liu, C., Tsai, C., Liu, J., Yu, C., and Yu, S. 2012. Pectoral Muscle Segmentation Algorithm For Digital Mammograms

Using Otsu Thresholding And Multiple Regression Analysis. *Comput. Math. with Appl.* 64(5): 1100-1107.

[36] Yang, J., Tseng, J., C., and Tseng, P., S. 2015. Path Planning On Satellite Images For Unmanned Surface Vehicles. *Int. J. Nav. Archit. Ocean Eng.* 7(1): 87-99.