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Segmentation Methods for MRI Human Spine Images using Thresholding Approaches

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ABSTRACT

Computer-Aided Diagnosis (CAD) in MRI image processing can assist experts in detecting abnormality in human spine image efficiently. The manual process of detecting abnormality is tedious, hence the use of CAD in this field is helpful to increase the diagnosis efficiency. The segmentation method is an important and critical process in CAD that could affect the accuracy of the MRI spine image's overall diagnosis. There are various segmentation methods commonly used in CAD. One of the methods is segmentation using thresholding. Thresholding approaches divide the area of interest by identifying the threshold values that can separate the image into desired grayscale levels based on its pixel's intensity. This study focuses on investigating the optimal approach in segmenting lumbar vertebrae on the MRI images. The steps involved in this study include pre-processing (normalization), segmentation using local and global thresholding, neural network classification, and performance measurement. 20 images are used to evaluate and compare the segmentation methods. The effectiveness of the segmentation method is measured based on the performance measurement technique. This preliminary study shows that local thresholding outperforms the global thresholding approach with an accuracy of 91.4% and 87.7%.

Keywords: CAD; MRI; image processing; segmentation; otsu

INTRODUCTION

A healthy human spine is important to provide support to the body. The human spine consists of five main sections: cervical vertebrae, thoracic vertebrae, lumbar vertebrae, sacral vertebrae, and coccyx vertebrae. Overall, there are about 33 vertebras in a combination of five main sections. Each of the vertebrae is separated and cushioned by an intervertebral disc (Wbaum et al. 2020). However, human might suffer from spinal diseases due to many factors such as wrong posture, accident, or aging. Among common spinal diseases are herniated disks, slipped vertebra, fractures and deformities (Dydyk, Massa and Mesfin 2020). These diseases are difficult to diagnose externally. Lumbar vertebrae is important to carry the weight of the body and is much larger in size to absorb the stress of lifting and carrying heavy objects. However, it was reported that 95% of herniated disks occur at the lower lumbar vertebrae (Jordon, Konstantinou and O'Dowd 2009). Thus, in this study, we focus on segmenting and classifying the intervertebral disk in lumbar vertebrae (L1 to L5) of spine MRI.

One of the medical imaging modalities used by experts to diagnose these diseases is Magnetic Resonance Imaging (MRI). MRI procedure provides images of the internal parts of the body such as organs and bones, hence the experts can use these images to diagnose the diseases. MRI scans are divided into two categories, T1 and T2 weighted scans. T1-weighted scans produce dark image for any part filled with water and brighter images for soft tissues with high fat concentration. Whilst, T2-weighted scans produce dark images for soft tissues with high fat concentration and brighter images for any part filled with water.

Computer Aided Diagnostic (CAD) system for MRI image processing could help specialists detect abnormalities of the human spine efficiently. The CAD system can analyze and improve the accuracy of diagnosis by increasing the sensitivity in the detection and characterization (Doi 2005). With the emerging technology nowadays, the research in automated image analysis for detection and segmentation of vertebrae utilizing CAD system has become in demand. However, achieving a fully automated detection and segmentation system is a challenging task. Most previous works such as in (Rangayyan, Deglint and Boag 2006; Ling et al. 2016) require prior information of vertebrae location. There are five important processes in CAD system: pre-processing, segmentation, extraction, classification, and performance measurement (Michopoulou 2011).

The segmentation process in CAD plays an important role to get a high precision image for diagnosis. Segmentation divides MRI images into desired regions, intending to enhance the targeted region of interest in the image. However, developing a segmentation algorithm that is efficient is very challenging. MRI images that have low-contrast and non-uniform background affect the efficiency of the segmentation process and thus contribute to the deficiency in diagnosis result. The artifacts and noises that are caused by physiological motions during the acquisition process degrade the quality of the images (Hirokawa et al. 2008). Previous research has worked on improving the quality of the MRI images by applying filters such as wavelet transform to enhance the images (Baseri Huddin et al. 2017). In addition, the problem in determining the position of the vertebra spine also affects the effectiveness of the segmentation method. This is because the spine has a complex composition of fat, water, soft tissue, and cartilage. In order to solve that, we are motivated to investigate segmentation methods that are usually used for detecting the abnormalities of MRI spine images.

Several segmentation methods for MRI human spine have been proposed. Most work require manual intervention to locate the center of the spinal cord before the segmentation is done (Hoad et al. 2001; Rangayyan, Deglint and Boag, 2006; Michopoulou et al. 2009; Barbieri et al. 2015). The manual process is time consuming for a huge amount of MRI spine cases. There are also work proposed for a fully automatic MRI vertebrae segmentation, that such are worked by (Peng et al. 2005) and (Chevrefils et al. 2009). However, work in (Peng et al. 2005), requires several pre-processed steps including the selection and the labelling of the vertebrae on MRI images. Although the work achieved a high detection accuracy, the work was performed on only six selected MRI images. Work in (Chevrefils et al. 2009) proposed an automated segmentation based on basic morphological operations and Otsu's thresholding to segment vertebrae on the MRI images. The segmented areas were then classified using k-NN classifier and achieved an accuracy of 88%. Segmentation of MRI images can be performed based on the pixel information of the images, such as super-pixel technique (Barbieri et al. 2015), watershed technique (Roberts, Gratin and GH. Whitehouse, 1997; Bazila and Mir, 2014), and thresholding (Barbieri et al. 2015). Another approach is based on the texture analysis of the MRI images (Chevrefils et al. 2009).

In this paper, two thresholding methods for segmentation of MRI spine are studied. The main contribution of this paper is to demonstrate the effect of thresholding values on the segmentation process of MRI spine automatically. The two thresholding approaches which are global and local are evaluated and compared based on the classification performance. The comparison is based on the classification of the features that are extracted from the vertebrae candidates. In this pre-liminary work, the features extracted are the shape features, i.e area, diameter, centroid, and the perimeter (Effa Adrina et al. 2017). The shape features are chosen due to the distinguishable morphological of vertebrae in the MRI images.

METHODOLOGY

In this paper, 20 MRI spine images were chosen as a dataset to perform segmentation using several thresholding techniques. These images were collected and contributed by our collaborators in the Department of Radiology, HUKM. The chosen images are limited to only sagittal views and focusses on the lumbar part of the spine.

Commonly, there are five important processes in CAD, which are pre-processing, segmentation, extraction, classification, and performance measurement as depicted in Figure 1. Each of the images will undergo these five processes, where the details of each process is explicitly explained in this section.

PRE-PROCESSING

In pre-processing, normalization technique is applied. Normalization process changes the range of pixel intensity values, without changing the information contained in the images. Normalization technique is sometimes called as dynamic range expansion. The purpose of the dynamic range expansion in application of gray-scale image is usually to bring the image into a specified range so that a consistent pixel-range within all the images is achieved. The normalization of grayscale image is performed linearly according to (1).

$$I_N = \frac{I - I_{min}}{I_{max} - I_{min}} \tag{1}$$

where I is the pixel value of the original image, I_N is the pixel value of the normalized image, I_{min} and I_{max} are the minimum and maximum pixel value in the image, respectively

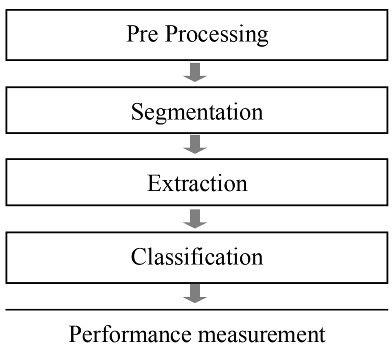


FIGURE 1. Flowchart for processes in CAD

The acquired MRI spine image has the color of grayscale, which has a dynamic range of pixel intensity. Normalization process changes the pixel intensity values to be in the range between minimum and maximum of [0,1]. The minimum range is zero in which represents the black color while the maximum range is one in which represents the white color with any fractional value within that numerical range.

Figure 2 (a) and 2 (b) show the histogram of an image before and after applying the normalization process. The figures show that after normalization, a pixel image at a fractional value exists within its numerical range. However, the image of the MRI spine remains the same.

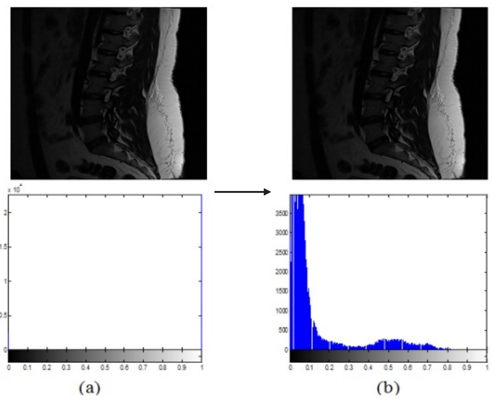


FIGURE 2. MRI image (a) histogram of original image (b) histogram of a normalized image

SEGMENTATION

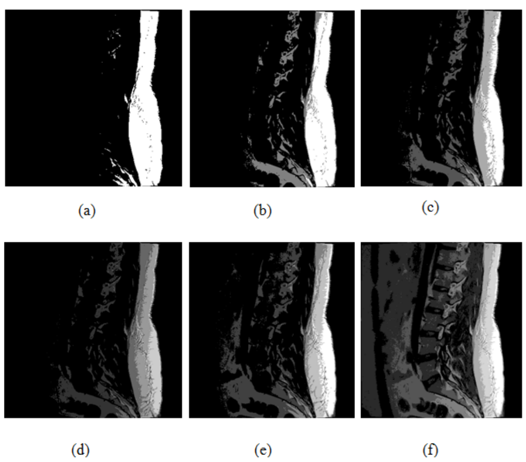


FIGURE 3. Segmented MRI images using (a) 2-level, (b) 3-level, (c) 4-level, (d) 5-level (e) 6-level and (f) 7-level Otsu

The thresholding technique is one of the simplest yet effective methods for segmentation and has been widely used in many applications, including medical images. The thresholding techniques is used to separate an image into the desired number of regions based on the distribution of gray levels in the image. For example, a grayscale image (i.e image with pixel values from 0 to 255) may be converted into a binary image (i.e image with pixel value 0 or 1) by segmenting it into two regions of colorscale e.g black and white.

This is achieved by applying a threshold value to separate the image's pixel values into those two regions. In other words, the pixel value that is less than the threshold value is set as 0 (black), and any pixel value that is more than the threshold value is set to 1 (white). The thresholded image $g(x,y)$ of an image with pixel value, $p(x,y)$ may be expressed as:

$$g(x,y) = \begin{cases} 1 \text{ for } p(x,y) > t \\ 0 \text{ for } p(x,y) \le t \end{cases} \tag{2}$$

where t is the threshold value.

The threshold value is determined by optimizing the specified criterion function such as minimizing the intra-class variance in Otsu's method, or by using the statistical information of the images such as entropy, mean, and standard deviation to separate the object from the background (Chen *et al.* 2018). Thresholding techniques can be applied globally or locally to an image. Global thresholding applies a single thresholding value, t to an entire image. A local thresholding technique applies different threshold values for different regions of an image (Senthilkumaran and Kirubakaran, 2014).

A. GLOBAL THRESHOLDING – OTSU METHOD

Thresholding using Otsu is one of the common techniques in segmenting images. Otsu thresholding offers multiple levels of segmentation areas. In Otsu's method, the segmenting is done on the basis of the distribution of gray level in the image. In a 2D grayscale image, it contains $N \times N$ pixels that each has gray level, i ranges from $[1, ..., L]$. Thus, the number of pixels with gray level i is denoted as f_i. The probability p_i of gray level i in an image can then be found as:

$$p_i = \frac{f_i}{N} \tag{3}$$

Otsu's thresholding aims to find a threshold to separate between classes by minimizing the between-class variance. In the case of two-level Otsu thresholding, the pixels in the image are divided into two classes, C_1 and C_2. Here, the first class, C_1 contains gray levels of $[1, ..., t]$ and the latter class, C_2 contains gray levels of $[t + 1, ..., L]$. To find the threshold value, t, the Otsu method calculates the between-class variance, σ_B^2 using the following equation:

$$\sigma_B^2 = \omega_1(\mu_1 - \mu_T)^2 + \omega_2(\mu_2 - \mu_T)^2 \tag{4}$$

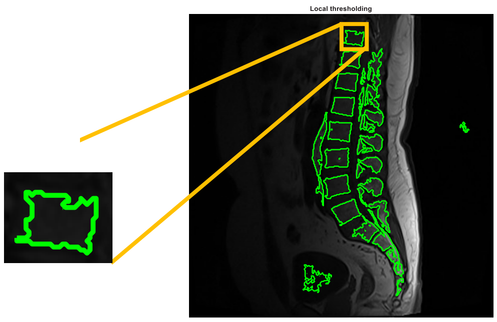


FIGURE 4. Detected vertebrae regions

GURE 4. Detected vertebrae regions

where, $\omega_1(t)$ and $\omega_2(t)$ are the sum of gray level probability distribution in classes C_1 and C_2, respectively. μ_1 and μ_2 are the means for classes C_1 and C_2, respectively. μ_T is the mean intensity for the whole image.

The Otsu method recursively finds the optimal threshold value, t so that the between-class variance σ_B^2 is minimized. This algorithm can also extend to a multi-level Otsu thresholding. Suppose the image is thresholded into classes. Otsu method applies the above equation to find $M - 1$thresholding values, $\{t_1, t_2, \ldots, t_{M-1}\}$ to segment an image into classes.

Figure 3 shows resulting thresholded MRI images using (a) 2-level, (b) 3-level, (c) 4-level, (d) 5-level (e) 6-level and (f) 7-level Otsu thresholding method. In this study, it was observed that 6-level thresholding improved the visual appearance for lumbar vertebrae on MRI images.

B. LOCAL THRESHOLDING – NI-BLACK METHOD

If an image has non-uniform background, a single value of threshold may not be suitable to apply to an entire image for segmentation. A thresholding algorithm that is adaptive to a small region may be used. This is also known as local thresholding method. One of the method is Ni-Black algorithm, where the algorithm determines the threshold value based on the local mean and the local standard deviation over a specific window size (Rais, Hanif and Taj, 2004).

In Ni-Black algorithm, the local threshold, t at any pixel (i,j) is found by using the following equation:

$$t(i,j) = m(i,j) + k\sigma(i,j) \tag{5}$$

where, $m(i,j)$ and $\sigma(i,j)$ are the mean and variance of the local pixel, respectively. Whereas, the value k in the equation is the fixed weight that is used to control the effect of the standard deviation upon noise in the background (Rais, Hanif and Taj, 2004; Senthilkumaran and Kirubakaran, 2014).

FEATURES EXTRACTION

The detected region's shape features are used for classification to classify them as vertebrae or the background. Figure 4 shows an example of one of the detected 'vertebrae' resulted from the segmented image using Ni-black local thresholding algorithm.

The shape features such as the area, A, perimeter, P, centroid, c and the diameter, d of each of the region are extracted using the formulae as in Table 1, where x and y are the coordinates of the pixel on the images.

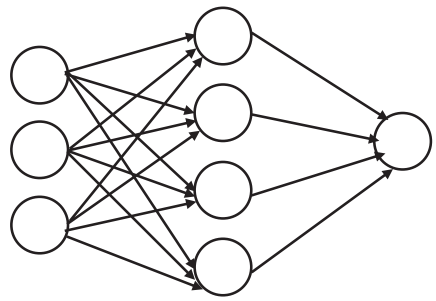


FIGURE 5. General diagram of a feed forward 3-layer neural network

TABLE 1. Vertebrae Shape Features

Features	*Equations*
Area	$A = \iint I(x,y)dy\,dx$
Perimeter	$P = \int \sqrt{x^2(t) + y^2(t)}\,dt$
Centroid	$c = \frac{1}{2}\sum_{i=0}^{n-1}(x_i y_{i+1} - x_{i+1}y_1)$
Diameter	$d = \frac{c}{\pi}$, where c is the centroid

PERFORMANCE MEASUREMENT

In this study, the segmented region classification is performed using a supervised classifier named neural network. Neural network is one of the most used classifiers for various image classification tasks (Hui *et al.* 2019; Rosario, 2019). The ability of neural network to perform classification on complex data pattern is one of the reason it has been chosen to assist, specifically in many medical applications (Effa Adrina *et al.* 2017; Assyareefah Hudaibah *et al.* 2019), (Awan *et al.* 2019).

The shape of features from each image is calculated and fed into the neural network to classify whether the segmented area belongs to the vertebrae or the background. The ground truth is also provided manually by the radiologist for result validation purposes. Thus, the neural network's input layer is directly connected to the shape features of the segmented region.

The classification is to determine whether the segmented area is categorized as vertebrae or the background. Thus, the neural network output is represented as: vertebrae images by '1' and background images by '2'.

The neural network used in this study has 3-layer, input layer, hidden layer, and output layer. **Error! Reference source not found.** depicts a general diagram of a feed-forward 3-layer neural network. The neural network architecture used in this experiment is as follows: the hidden layer contains 10 neurons and one node in the output layer. Sigmoid function, $\sigma(x)$ is chosen as the activation function for this neural network. The number of image samples is randomly divided into 3 parts; 60% for training, 5% for validation and 35% for testing. The training phase in neural network is performed on a 6-fold validation. This is to avoid an overfitting situation in the training phase.

After classification is performed, we can analyze the Otsu method based on performance measurement. There are two measurement such as Receiver Operating Curve (ROC) and confusion matrix. A true positive (TP) is a case that is classified as abnormal and in reality, it is abnormal. A true negative (TN) is classified as a normal case and in reality, it is normal. A false positive (FP) is a case that is classified as abnormal but the reality, it is normal. A false negative (FN) is a case that is classified as normal but in reality, it is abnormal. The sensitivity or the true positive rate (TPR) of the system can be found by the formula:

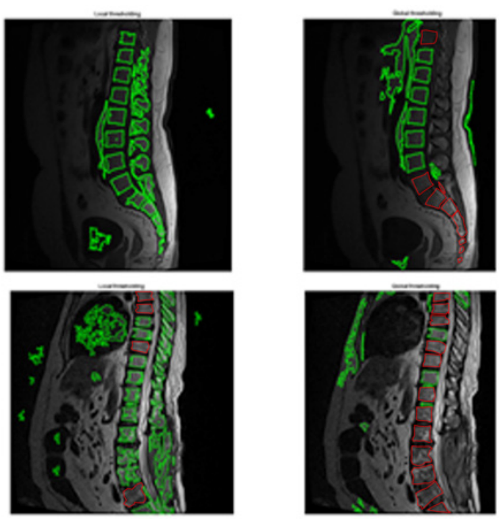
$$\mathrm{TPR}=\frac{TP}{TP+FN} \tag{6}$$

Whilst false positive rate (FPR) can be found by the formula:

$$\mathrm{FPR}=\frac{FP}{FP+FN} \tag{7}$$

RESULTS AND DISCUSSION

The performance measurement of segmentation using both local and global thresholding methods are evaluated and compared. Both methods are tested on the same 20 MRI image databases. The results of the segmentation methods can be evaluated in qualitative and quantitative measures.



(a) (b)

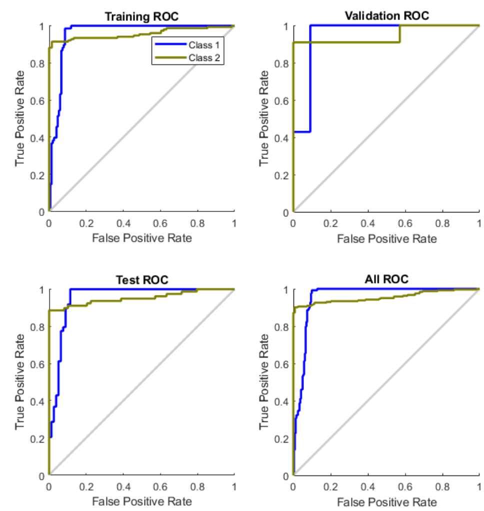
FIGURE 6. Segmented MRI images using (a) Ni-black local thresholding and (b) 6-level Otsu global thresholding

Figure 6 (a) and (b) show two MRI spine cases that are marked with the detected vertebrae using local and global thresholding methods, respectively.

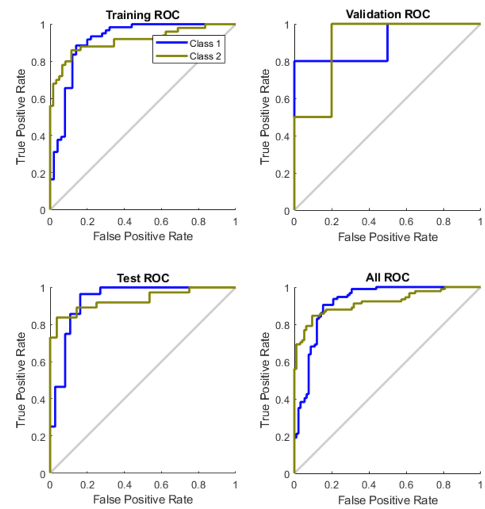
The green outline represents the areas detected automatically by the system, while the red outline represents the ground truth marked by the radiologist. Quantitatively, the result shows that the Ni-black thresholding technique detects more vertebrae than the global Otsu thresholding.

Qualitatively, the performance of the segmentation methods is measured using neural network classifier. Neural network is used to classify the segmented region as vertebrae, or non-vertebrae based on the shape features extracted from the region. The accuracy of the system is compared with the ground truth provided by the radiologist.

Figure 7 shows the ROC of the neural network classification of the segmented vertebrae using local and global thresholding methods. The classification is true positive (TP) if the detected region of vertebrae is correctly classified. Whilst it is true negative (TN) if the background



(a)



(b)

FIGURE 7. ROC curve for classification of segmentation method based on (a) Ni-black local thresholding and (b) Otsu global thresholding. Class 1 represents the vertebrae and Class 2 represents the background.

is correctly identified as the background. The ROC is plotted based on the sensitivity of the system against the false positive rate using the formulae (6) and (7).

The results show that local thresholding segmentation method, Ni-black method, achieves an accuracy of 91.4%. Whereas, when using global thresholding method, Otsu method, the classifier achieves 87.7% of classification accuracy. This result showed an improved detection accuracy when Ni-black's local thresholding technique was used to segment the vertebrae. The result obtained also showed a comparable finding compared to the previous work as in (Chevrefils *et al.* 2009), where they used Otsu's thresholding and achieved an accuracy of 88%.

CONCLUSION

The preliminary result of this work shows that the choice of segmentation method in image processing technique for diagnosing MRI spine is crucial and affects the overall classification performance. The simple yet effective segmentation technique, thresholding, has been a popular choice for the purpose. The technique ables specific segments of the region of interest and has the advantage of extracting valuable and essential features precisely to diagnose the MRI spine correctly. However, suitable thresholding techniques are crucial to achieving the high accuracy of detection. This work has demonstrated the effect of local and global thresholding for accurate spine detection that can be part of the fully automated diagnosis system.

In future, it is aimed to explore the ability of deep learning neural network, where the feature extraction process is automatically done in the network, without the need of segmenting the region of interest.

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DECLARATION OF COMPETING INTEREST

None

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