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Knowledge-based adaptive thresholding segmentation of digital subtraction angiography images

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Abstract

Vessel segmentation is the base of three dimensional reconstruction on digital subtraction angiography (DSA) images. In this paper we propose two simple but efficient methods of vessel segmentation for DSA images. The original DSA image is divided into several appropriate subimages according to a prior knowledge of the diameter of vessels. We introduce the vessels existence measure to determine whether each subimage contains vessels and then choose an optimal threshold, respectively, for every subimage previously determined to contain vessels. Finally, an overall binarization of the original image is achieved by combining the thresholded subimages. Experiments are implemented on cerebral and hepatic DSA images. The results demonstrate that our proposed methods yield better binary results than global thresholding methods and some other local thresholding methods do.

Keywords: Digital subtraction angiography; Adaptive threshold; The busyness

1. Introduction

Digital subtraction angiography (DSA) is a well-established modality for the visualization of blood vessels in the human body [1]. Vessel segmentation in DSA forms an essential step in several practical applications such as diagnosis of the vessels and registration of patient images obtained at different times.

Thresholding is one of the old, simple and popular techniques of segmenting images consisting of bright objects against dark backgrounds or vice versa [2,3]. Image binarization methods can be divided into two classes: global and local thresholding techniques. The simplest and earliest method is the global thresholding technique, but it is not applicable on some occasions. Take example for images consisting of bright objects against dark backgrounds, some parts of the objects may be darker than certain regions of the background. In that case, any fixed threshold level for the entire image usually fails to separate the objects from the background. Thus, global thresholding techniques [4,5] have likewise been found to be unsatisfactory for DSA images which are usually unimodal with a very narrow peak.

Locally adaptive binarization methods, on the other hand, calculate a threshold at each pixel depending on some local statistics like range, variance, or surface-fitting parameters of the pixel neighborhood [6]. Some of the methods partition the original image into smaller subimages and determine a threshold for each of the subimages. For X-ray angiograms Fernando and Monro [7] suggest a local thresholding method to partition the original image with 16 non-overlapping subimages and determine the

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threshold value for each of the subimages. In the local method of Bernsen [8], the threshold is set at the midrange value, which is the mean of the minimum and maximum grey values in a local window of suggested size $w = 31$. However, if the contrast in the neighborhood window is below a certain threshold, then that neighborhood is said to consist only of one class, objects or background. The method from Niblack [9] adapts the threshold according to the local mean and standard deviation and calculated a window size of $b \times b$. Francis et al. [10] proposed a new adaptive thresholding method which can be viewed as a variational translation of Yanowitz and Bruckstein's algorithm [11]. Since the DSA images have poor local contrast, inhomogenous background, varying vessel width, the above-mentioned local adaptive binarization methods are not applicable to segment DSA images.

In our previously proposed method [12], a threshold at each pixel is calculated depending on some local statistics like range and variance difference in double neighborhood windows. The calculation of a threshold at each pixel takes much time and the efficiency of the algorithm needs improvemation. Besides, we previously proposed another method with overlapping subimages in [13]. A hypothesis test is used to determine whether each subimage contains vessels, and subimages determined previously to contain the vessels are binarized with a secondary validation.

In this paper, we design two simple but efficient methods for vessel segmentation of DSA images using adaptive thresholding techniques. Aiming at the difficulties in choosing a proper threshold for subimages in which vessels occupy much less area than the background does, the original image is divided into overlapping subimages, which takes into consideration the pixel intensities information in the neighborhood subimages to choose an optimal threshold for the subregion under consideration. Hence, the limitation of the normal thresholding methods with non-overlapping subimages that the local binarization methods behave like the global thresholding methods in some subimages is improved. The size of subimages is constrained according to a priori knowledge of the diameter of vessels to make sure that each subimage contains the background definitely. Since there are only two possibilities about every subimage, we introduce the vessels existence measure to determine whether each subimage contains vessels, which avoids the noise resulting from the binarization of subimages only containing the background. We combine the binarization of the overlapping images to threshold the common regions of them. And the partial results are combined to yield an overall segmentation. We compare these segmentation results with the ones yielded by global thresholding techniques and some other local thresholding methods. We find out that our methods have yielded preferable segmentation results and are much more efficient than some local thresholding techniques computing a threshold for each pixel in the original image do.

2. Methods

We assume that the images contain dark objects and bright background. Therefore, thresholding at a particular threshold T leads to a binary image in which pixels with intensity lower than or equal to T are marked as object pixels and all other pixels as background. Corresponding with the assumption, the thresholded image is a binary image in which the pixel intensity of objects is 0 and the one of background is 1. Our approaches under this assumption, however, can be easily adapted to handle image of bright objects with dark background.

First of all, the original image is divided into N non-overlapping subimages, as is shown in Fig. 1. Every $a \times a$ region E_l ($l = 1, \ldots, N$) is the common subregion of four $b \times b$ ones: b_{1l}(ABDE), b_{2l}(BCEF), b_{3l}(DEGH), b_{4l}(EFHI). We binarize b_{kl} ($k = 1$–4), respectively, and then combine the binarization of b_{kl} to get the segmentation result of the subregion E_l. We constrain a in such a range as $d < a < 2d$ and b in such a range as $a < b < 3a$, where d is assumed as the widest diameter of vessels. In that case every subimage is confirmed to include the background and the local thresholding behaving like the global thresholding is avoided.

We propose two methods to implement the binarization of subimages b_{kl}: (1) implement the vessels existence analysis and then choose an appropriate thresholding method to threshold subimages previously determined to contain vessels; (2) firstly, binarize subimages b_{kl} and then validate whether the previous thresholding is rational, which means to examine previously binarized subimages to retain the binarization of subimages containing vessels and mark all the pixel intensities in subimages containing only the background as 1(logical value). Finally, we combine the binarization of b_{kl} to threshold the subregion E_l.

The flow charts of the two adaptive thresholding methods are shown in Fig. 2a and b.

In the first flow chart, we use the variance measure to complete the process of vessels exsistence analysis, whereas, in the second one we utilize the busyness measure [14] to implement the process of validating the rationality of previous binarization of subimages b_{kl}. In this paper we choose a simple but effective threshold method, the Otsu method [15], to binarize subimages.

We will illustrate the two methods, respectively, in the following part.

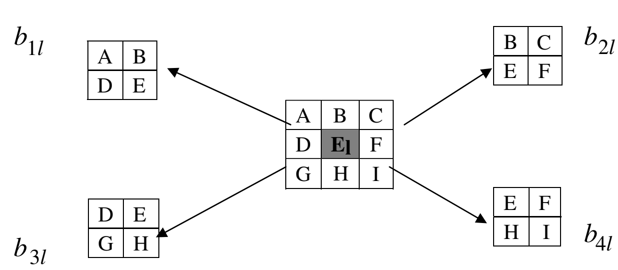

Fig. 1. The location relationship of E_l and b_{kl}.