BIOMEDICAL IMAGE SEGMENTATION BASED ON SHAPE STABILITY

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ABSTRACT

Biomedical image segmentation remains a challenging task mainly due to the weak edges and unevenly distributed color intensity of the objects and background. We present a novel unsupervised segmentation method to extract nuclei region from background. Our method, called shape stability algorithm, is a multiscale local adaptive threshold method. A modified weighted filter which serves as preprocessing method is also introduced. The presented algorithm is applied for segmentation of a number of Pap Smear images as well as bone marrow cell images. The results indicate the successful performance of the presented segmentation algorithm in segmentation of both Pap Smear and bone marrow samples.

Index Terms— Image segmentation, Biomedical image processing

1. INTRODUCTION

Image segmentation is one of the most fundamental and challenging tasks mainly due to the weak edges and unevenly distributed color intensity of the objects and background. Only based on an accurate segmentation can meaningful cell feature be extracted.

The shape stability segmentation algorithm, introduced in this paper, was developed based on a simple observation over the human visual system. The role of intensity in distinguishing objects by human eyes can be modeled and described using the concept of object detection quantum efficiency introduced by Rose [1]. This well-established model, heavily used in the study of human visual system, states that: $B \times C^2 \times \alpha^2 = constant$, where B is luminance, C is threshold contrast, and α is the object size. According to this model, for a certain size of object with given luminance, the true shape of the object can be distinguished only if the contrast between the object and the backtround is big enough. This in turn implies that a good threshold in intensity difference between the object and the background is the one that preserves the shape of the object.

The granulometric method [2, 3], partially inspired by the above observation, is a morphology multiscale method that provides a decomposition of an image based on scale with increasing criterion. Here we apply a similar concept of multiscale method without having an increasing criteria on size or shape. The component trees method [4] uses a tree structure to represent segmentations under certain thresholding where area and eccentricity were used to find qualified segmentations. Our method differs from the component trees by using the optimal derivative of $\frac{\phi}{intensity}$, ϕ is the integrated index used to describe the expected shape of the object, for each connected component to find the optimal threshold that can best segment the object from the background while "preserving the expected shape". Thus, we are not only looking for a regular shape, but also a stable shape when the threshold is changing. We will present the methodology followed by experiments results in the following sections.

2. METHODOLOGY

2.1. Preprocessing

In many cell images and in particular the cervical cells in Pap Smear images, nuclei have the darkest colors. In cytological studies, nuclei are often considered as the most informative regions. In addition, in cell image segmentation and analysis, features such as area, density, texture, and shape are often more reliably calculated for nuclei. For instance, the nuclei features are heavily used in cell classification standards such as The Bethesda System (TBS) [5].

Segmentation of cell and nuclei depends highly on the preprocessing step that is often specialized towards the needs and requirement of the main segmentation method. The presented method in this paper includes a preprocessing stage using an extension of median filtering based on the concept of "weighted median filter" illustrated in Figure1.

Weighted median filter, introduced by Brownrigg [6], provides flexibility in changing the number of copies of an element in the sorted array. The Brownrigg's median filter has weights on any position of the filter depending on the number of times the element is copied to a sorted array. The "modified weighted filter" forms uniform regions while conserving the edge information. Besides the "weight index" (WI) as the original weighted median filter, the modified weighted filter also has a "shift index" (SI) allowing the user to pick the

7	3	4
5	1	6
6	6	1

(a) The pixel value under the filter of size 3×3

$1134\boxed{5}6667$

(b) $WI = 1$

$11113\boxed{4}56667$

(c) $WI = 3$

$1134\boxed{5}6667$

(d) $SI = 0.5$

$1\boxed{1}3456667$

(e) $SI = 0.2$

Fig. 1. Weight index represents the hardness of changing the values in the modified weighted filter, shift index represents the shifted tendency towards background or foreground

$\lfloor SI \times FilterSize \rfloor th$ element in a sorted array which is generated from the elements under the filter. Basically, it allows the user to set bias for pixels and therefore to prefer "darker" or "brighter" regions. In a binary image, the open filter and the close filter are the specific cases of the modified weighted filter when the shift index is set to 0 or 1. It can be seen that the Brownrigg's weighted median filter is a specific case of our modified weighted filter with shift index set to 0.5. By adjusting the value of the shift index, the modified weighted filter can provide a less aggressive performance comparing to a standard open or close filter.

Combining weight and shift index, the modified weighted filter can have some flexibility that provides better filtering performance in our presented cell image segmentation. The modified weighted filter is used twice during the processing. It is first applied to the gray scale image (smoothing). Then, the gray scale image is thresholded on different values to produce a series of binary images. A modified weighted filter is applied to these binary images to fill holes and remove extra small regions.

The pre-processing of image before segmentation is shown as:

1 Transform color image to gray scale image
2 Use modified weighted filter to smooth image
3 Threshold gray scale image (on certain intervals) to produce a chain of binary images
4 Use modified weighted filter to eliminate holes and small regionsale
5 Eliminate over sized segmentation
6 Continue in Section 2.4

2.2. Optimization of threshold range and threshold interval

There are three typical regions in cell images: nucleus, cytoplasm and background, with color from dark to bright. The max variance threshold algorithm developed by Otsu [7] is recursively used three times to obtain three threshold values $v1$, $v2$ and $v3$ which roughly thresholds nucleus / nucleus+cytoplasm /cytoplasm+background/background. The best threshold value falls in the range $[v3, v1]$. However, starting from these initial points, we design our optimization process to find optimal threshold values for each nucleus. It is expected that the best threshold value to separate cytoplasm from nucleus falls in $[v3, v2]$. Other than testing every value in $[v3, v1]$ for the optimal thresholding results, the searching interval is selected in a geometric sequence such that the gray levels closer to $v2$ have smaller threshold interval and therefor better resolution.

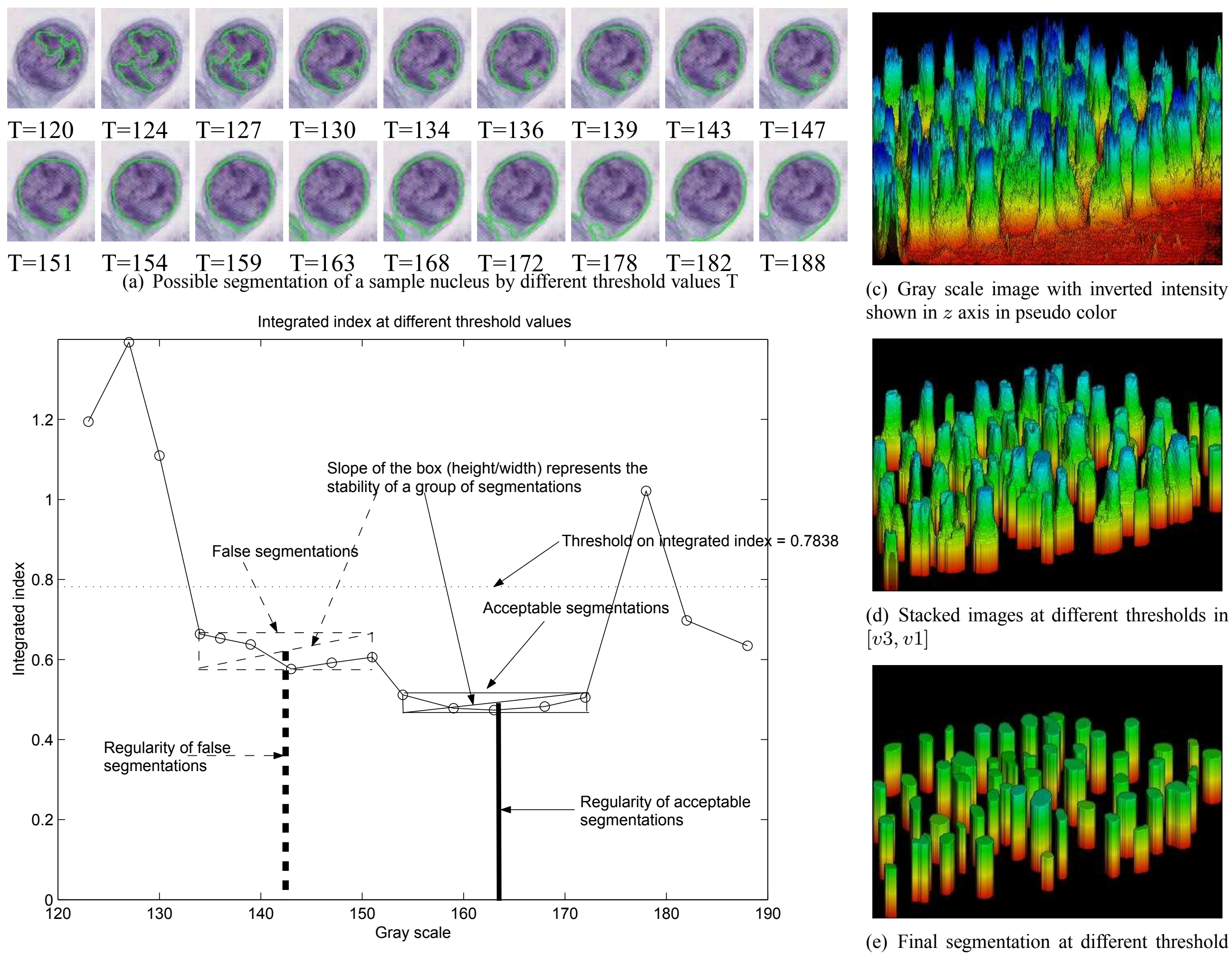
2.3. Optimization of shape indices

The next step is to search for a suitable criteria to find the optimal threshold value among the above-mentioned candidates. In order to evaluate and score a segmentation technique based on its capability to preserve the shape of objects (as intended in our segmentation technique), one needs to select features and criteria to measure the degree at which the known shape of the segmented object is preserved. The ground truth of the nuclei is manually labeled. During the multiscale morphological translation, a chain of connected components from each nuclei is formed based on the threshold. Those segmentation having area differences less than 10% compared to the ground truth form a "regular" set for each nuclei. The rest of the segmentation form "irregular" set. By evaluating the shape features (normalized radius length (NRL) standard deviation, entropy, area ratio, zero-crossing count, circularity, compactness, eccentricity, fractal dimension and Fourier descriptors) of the circular objects often seen in medical images [8], we find that the normalized compactness ($NC = \frac{(contour\_length)^2}{area_{ROI}}$) is the most distinctive index that best distinguishes the correct segmentation of a regular shape from ill segmentation of irregular shapes of nucleus.

In order to provide a better criterion, we first define a new index named region expanding rate (RER) as:

$$RER = \frac{\sqrt{\frac{A_n}{A_{n-1}} - 1}}{T_n - T_{n-1}} \tag{1}$$

where n is the level of thresholding, A_n is the area of a certain segmented region and T_n is the threshold value. The region expanding rate measures the percentage increase in radius per gray scale. Our integrated index $\phi = \sqrt{NC^2 + \alpha RER^2}$ combines the index of normalized compactness and the index of region expanding rate to provide a better performance where the α is a scalar factor calculated based on the performance each feature such that the index with larger distinguishing power will have larger contribution to the overall evaluation.



(a) Possible segmentation of a sample nucleus by different threshold values T

(b) Integrated index changing on different threshold values

(c) Gray scale image with inverted intensity shown in z axis in pseudo color

(d) Stacked images at different thresholds in $[v3, v1]$

(e) Final segmentation at different threshold for each nuclei

Fig. 2. Possible segmentation and integrated index value on different threshold values with $\beta = 0.7838$

2.4. Choose segmentation value based on the shape stability

Figure 2 shows the segmentation with different threshold values and the integrated index corresponding to each threshold value. Choosing "the best segmentation" solely on the lowest integrated index value may result in a non-optimal segmentation because some false segmentation happen to have a regular shape thus having a low integrated index value. The presented algorithm focuses on searching for a series of acceptable segmentation as opposed to just one segmentation with minimal index value.

The acceptable segmentation are formed by a chain of thresholding values and are defined as a set of segmentation having small integrated index values as well as a small slope named the stability of the window (STB), defined as

$$STB = \frac{\max(\phi) - \min(\phi)}{\max(ThresholdVal) - \min(ThresholdVal)} \tag{2}$$

The threshold window size is determined in the range of $[\lceil \frac{N}{4} \rceil, \lfloor \frac{N}{2} \rfloor]$ where N is the number of consecutive values of where integrated index $< \beta$ and $N \geq 5$ where β is the value with 2.5 standard deviation form the mean integrated index of regular shapes so that 99.9% regular shapes will fall within the threshold. This window size is based on the statistics of the number of acceptable segmentation by choosing the average number of acceptable segmentation as the maximum window size and about half of the maximum window size as the minimum window size. We first locate the "acceptable segmentation" within the window with minimum STB value, then pick the one having the minimum ϕ. Figure 2(c) shows the gray scale image with inverted intensity shown in z axis in pseudo color.

Table 1. Statistics of performance of different algorithms

Algorithm	TN (%)		TP (%)	
	μ_X	σ_X	μ_X	σ_X
Shape stability	98.44	1.22	78.93	12.10
Mean shift with shape guidance	98.84	1.28	56.86	22.95
Marker controlled watershed	95.18	3.40	74.20	19.48

$F - Test$ significant for $\alpha = 0.01$ for both true positive (TP) and true negative (TN)

Figure 2(d) shows the stacked image thresholding at different intervals in $[v3, v1]$. Figure 2(e) shows the final segmentation for each nuclei. As can be seen, the optimal threshold value is selected for each nucleus.

Now that every step of the algorithm has been described, the overall schematic diagram of the algorithm can be presented as:

1 Find optimized threshold range and threshold interval
2 Preprocess image (from Section2.1)
3 Threshold to get a serial of binary image for each threshold
4 Calculate shape stability index to find a group of acceptable segmentation candidates
5 Select best segmentation from acceptable segmentation candidates

3. RESULTS

We compare the presented method with the mean shift algorithm and the marker controlled watershed algorithm with marks selected by Pikaz's algorithm [9] for Pap Smear test images and the results are listed in Table 1 from 37 images each has dozens of cells with different pathological conditions. The segmentation are compared with manually labeled ground truth represented in true positive (TP) and true negative (TN). $F - test$ was conducted and showed there exists significant performance differences among these three algorithms and the shape stability algorithm proves to outperform the other two methods.

4. CONCLUSION

The modified weighted filter provides a more controlable performance comparing to a standard open, close, median or weighted median filter which works for both grayscale and binary image. By using the STB to find the optimal threshold value, the segmentation is not only regular according to the shape criteria, it is also the most stable segmentation when the threshold value is changing. Our method uses grayscale image outperforms the mean shift method which uses color image. This indicates that the pattern information does not lose when project the color image to grayscale image if the transformation is selected correctly for the perpose of segmentation.

The threshold based segmentation method is considered as well developed, robust yet simple method facing the challenge of inhomogeneous background. Our multiscale threshold method with shape stability functions as criterion of selecting threshold value is adaptive to the spatial variance of intensity and the shape of the object is preserved. The presented method based on the stability of shapes has shown to have robust performance on cell images having large variations in the color contrast between the objects and their local backgrounds. The shape stability can be applied to other kind of shapes as long as there exists a shape criteria to distinguish the interested shape from the others.

5. REFERENCES

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