Nigerian Research Journal of Engineering and Environmental Sciences 3(1) 2018 pp. 32-38

Nigerian Research Journal of Engineering and Environmental Sciences
Journal homepage: www.rjees.com

Original Research Article

PARTITIONED GRAPH CUT SEGMENTATION ON HETEROGENEOUS CELL IMAGES

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ARTICLE INFORMATION

Article history:
Received 17 May, 2018
Revised 23 May, 2018
Accepted 24 May, 2018
Available online 30 June, 2018

Keywords:
Cell segmentation
Graph cut
Heterogeneous cells
Partitioned graph cut
Segmentation

ABSTRACT

Heterogeneous cell images are currently posing great challenges in medical image segmentation. This is due to the fact that cells that constitute these images lack homogeneity. As a result, popular segmentation methods such as active contour, watershed, thresholding and graph cut do not perform well. In order to address this challenge, a partitioned segmentation of cell images is proposed using graph cut. First, cell images were broken into fairly homogeneous units and then graph cut segmentation was thereafter carried out on each individual partitioned unit. The segmentation results from these units were then merged. Experimental results show improved performance over traditional graph cut and state of the art models.

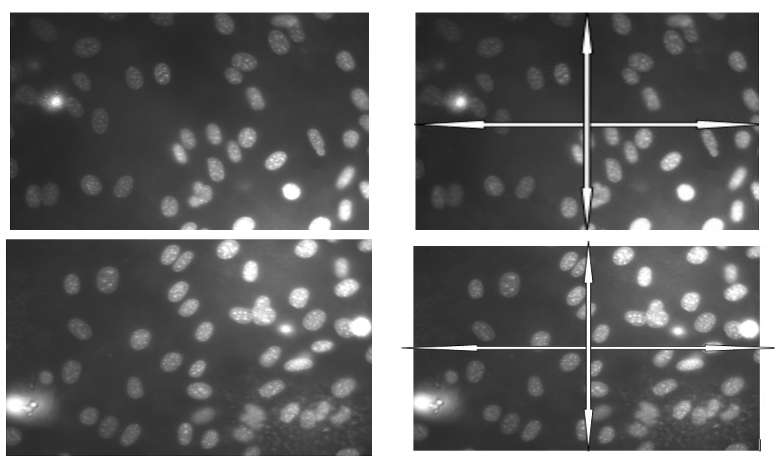
1. INTRODUCTION

Cell segmentation provides an opportunity to delineate objects of interest from the background towards effective analysis and diagnosis of specific medical conditions. There exists a variety of methods for cell segmentation: These include thresholding, active contour, watershed and graph cut (Chen and Pan, 2018). Among these methods, the graph cut is the most popular because it segments images in a global and optimum manner (Chen and Pan, 2018). Moreover, all other segmentation methods give satisfactory results on homogeneous cell images. However, cell images do not always appear homogeneous; their appearance is often a function of their acquisition processes. When cell images are captured in poorly lit conditions in order to preserve their natural characteristics, there is the likelihood to acquire non-uniform illuminated cell images. This acquisition process may result in cells images with high signal-to-noise ratio giving rise to heterogeneous cell images (Salah et al, 2011).

Many authors have leveraged graph cut for cell segmentation with good results. For example, cervical cell segmentation (Zhang et al., 2014) and live cell segmentation (Lesko et al., 2010) were case studies. However, the graph cut segmentation faces challenges when confronted with heterogeneous cells. This is because when the graph cut segmentation is initiated with inconsistent foreground and background sample pixels, an unsatisfactory result is obtained. In the light of this, research has been carried out to improve the segmentation output of graph cut on dense or heterogeneous cells. As an illustration, a two-stage graph cut segmentation was proposed by Danek et al. (2009). A graph cut segmentation, incorporating Local Binary Pattern (LBP) for the extraction of cell features was put forward in Song et al. (2013). In Chen et al. (2013) and Alilou et al. (2013), a template approach was proposed where a predefined object template was provided that guided segmentation. In Lin et al. (2003) and Coelho et al. (2009), a merging algorithm was introduced were portions of the object of interest were segmented and were thereafter merged. Also, methods such as thresholding, active contour and watershed have been experimented with for the segmentation of heterogeneous cell images (Coelho et al., 2009).

Heterogeneous cell images are often acquired as a result of non-uniform illumination and the non-uniform staining during cell acquisition process. This kind of images encapsulates a combination of bright cells, not too bright cells and cells fading to the background (Figure 1(a)). The challenge faced in automating heterogeneous cell segmentation is that it is often difficult to identify and segment actual cells from their background as they may have similar grey scale intensity level (Nielsen et al., 2012; Chen et al., 2013; Song et al., 2013). One of the characteristics of heterogeneous cell images as noticed in Figure 1 is that cells of same intensity values can be fairly partitioned into units of cells. An example is seen in Figures 1(a) and 1(b). If fairly homogeneous partitioned units can be derived from heterogeneous cell images, then segmentation can be carried out on each partitioned unit, independent of other units.

The idea of partitioned segmentation has also been influenced in the segmentation of objects (Lin et al., 2003; Roy and Biswas, 2015). Inspired by these methods, this study proposes partitioned cell segmentation on heterogeneous cell images. Partitioned graph cut segmentation approach is useful since the global segmentation approach of the traditional graph cut over an entire image (heterogeneous image) may be unsatisfactory (Figure 2). The ability to group heterogeneous cell images into fairly homogeneous units and carry out graph cut segmentation on each unit is the key contribution of this work. First cell segmentation is initiated by giving users the platform to select sample foreground and background pixels over a given image; then, the cell image is partitioned into fairly homogeneous units. Thereafter, the graph cut segmentation is carried out on each unit. The final segmentation is obtained by merging the results from each partitioned unit.



a b

Figure 1: (a) Original cell images (b) Partitioned cell images

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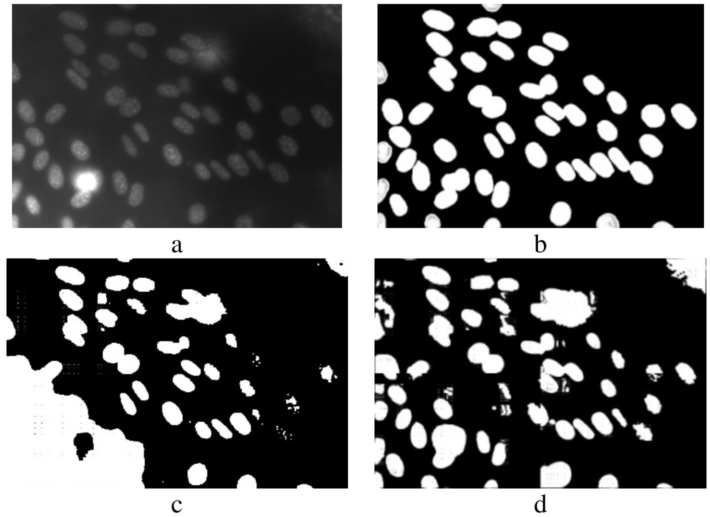


Figure 2: (a) Original cell image (b) Ground truth (c) Graph cut segmentation output (b) Proposed model segmentation output

2. METHODOLOGY

2.1. Graph Cut Concept

A graph ($G = (V, E)$) can be represented as a collection of pixels (*a,b,d,e,f,g, O,B*) as seen in Figure 3.

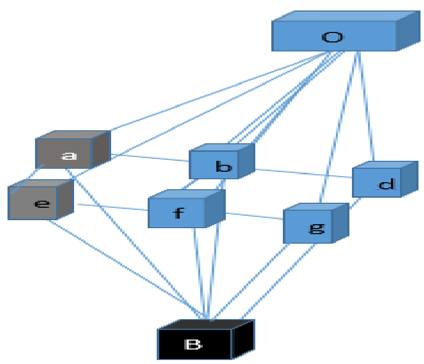


Figure 3: Image represented as a graph

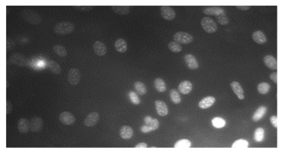
Pixels (nodes) *a,b,d,e,f,g,O* and *B* are found in the set *V* while edges of nodes (for example *b-O, b-d* and *b-B*) are found in the set *E*. Weight assignment to terminal node edges (for example *b-O* and *b-B*) is given using Equations (2) and (3) while weight assignment to neighboring node edges (for example *d-g* and *b-d*) is given using Equation (4). In Equation (2), *bg* is the brightness value of background pixels, while *fg* in Equation (3) is also the brightness value of foreground pixels. *fg* and *bg* which are manually selected interactively by the user are the foreground and background sample pixels respectively (Boykov and Jolly, 2001). In Equation (4), I_b and I_a are brightness values for pixels *a* and *b*. The Euclidean distance of *a* and *b* is given as *ed(a,b)* (Boykov and Jolly, 2001). λ ensures segmentation output is not over-segmented or under-segmented. The Algorithm in Boykov and Kolmogorov (2004) was used to segment a weighted graph *G* into foreground and background nodes/pixels.

$$E = \lambda R + C \tag{1}$$

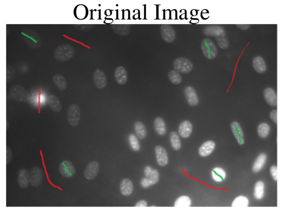
$$R = -log(Prob(I_b)|bg)) \tag{2}$$
$$\mathrm{R} = -log(Prob(I_b)|fg)) \tag{3}$$
$$C = \sum_{(a,b)E} \exp\left(-\frac{|\mathrm{I_a} - \mathrm{I_b}|^2}{2\sigma^2}\right) \tag{4}$$

2.2. Partitioned Graph Cut Segmentation

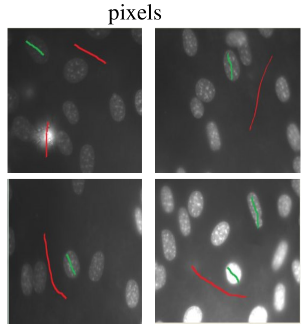
The proposed partitioned graph cut segmentation splits cell image into fairly homogeneous units, while carrying graph cut segmentation on each unit. Algorithm 1 gives a summary of the proposed model while Figure 4 graphically shows the proposed model.



Original Image

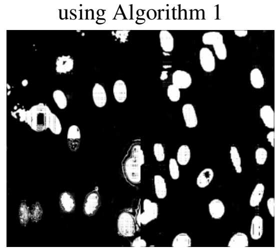


User selects sample foreground (fg) and background (bg) pixels



Partitioned image

Carry out graph cut segmentation on each partitioned unit using Algorithm 1



Merge segmented results from each partitioned unit

Figure 4: Summary of proposed model from top to bottom

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Algorithm 1*:* Partitioned Graph Cut Segmentation on Heterogeneous Cell Images

```
Require: I - Greyscale Image
Ensure: I_si-Segmented image
    User selects foreground sample pixels fg from I
    User selects background sample pixels bg from I
    Partition cell image into units and save each unit in P
for each unit u in P
    Construct graph G from u
    Use equations (2) and (3) to give weights to nodes in G in relation to their terminal nodes O and B.
    Use equation (4) to give weight to neighbouring pixels/nodes in G
    Using Algorithm in (Boykov and Kolmogorov, 2004), store graph cut segmentation of G in M
end
Merge all the segmented results from each unit in M to I_si
```

2.3. Dataset

Experiments were carried out on publicly available dataset NIH3T3 (Coelho et al., 2009). This dataset was adopted for evaluation based on its record in having heterogeneous cell images with high signal to noise ratio, which is suitable for this study.

2.4. Parameter Selection

In Algorithm 1, cell images are partitioned into four parts. Four is selected as it fairly partitions images into fairly homogeneous cells. However, for more complex heterogeneous images, more partitions are recommended.

3. RESULTS AND DISCUSSION

The proposed model was benchmarked using two metrics. These metrics are the Rand Index (RI) and F-score. Equations (5) and (8) define these metrics.

$$RI\ (\%) \frac{TP + TN}{(TP +\ TN + FP + FN)} \tag{5}$$

$$Sensitivity\ (S\ \%) = \frac{TP}{(TP +\ FN)} \tag{6}$$

$$Precision\ (P\ \%) = \frac{TP}{(TP +\ FN)} \tag{7}$$

$$F - score\ (\%) = 2(\frac{S * P}{(S +\ P)}) \tag{8}$$

True Positive (TP) identifies the total number of pixels that are foreground in the segmented image (S) and also seen as foreground pixels in the ground truth (GT). True Negative (TN) identifies the total number of pixels that are background in S and are also background pixels in GT. False Positive (FP) identifies the total number of pixels that are foreground in S but referenced as background in GT. False Negative (FN) identifies the total number of pixels that are background in S but referenced as foreground in GT. For metrics *RI* and *F-score*, high values give better segmentation output. Based on these metrics, the proposed model performed better than other existing models as observed in Table 1. In Table 1, the thresholding algorithm may have suffered from over-segmentation as it does not perform well on heterogeneous cell images.

Table 1: Comparison of the proposed approach with existing models

Models	RI (%)	F-score	Reference
Thresholding	74	-	Coelho et al., (2009)
Watershed (Direct)	78	-	Coelho et al., (2009)
(Song et al., 2013)	87	-	Song et al., (2013)
Merging algorithm	83	-	Coelho et al., (2009)
Interactive Graph Cut	87.28	73.0	-
Geodesic active contour	88.4	67.79	-
Proposed model	90.46	77.55	-

Table 2: Time Comparison of the proposed model with existing models

Models	Times (seconds)
Interactive Graph Cut	35
Geodesic active contour	65
Proposed model	90.46

This argument also holds for the geodesic active contour. In addition, the merging algorithm (Coelho et al., 2009) and the graph cut with LBP (Song et al., 2013) give good segmentation result; but, these methods do not provide the advantage of an interactive segmentation where users can manually select sample pixels as observed in Algorithm 1. As a result, there is a reduction in their performances as compared to the proposed model. Figure 5 also shows improved segmentation output over the traditional graph cut.

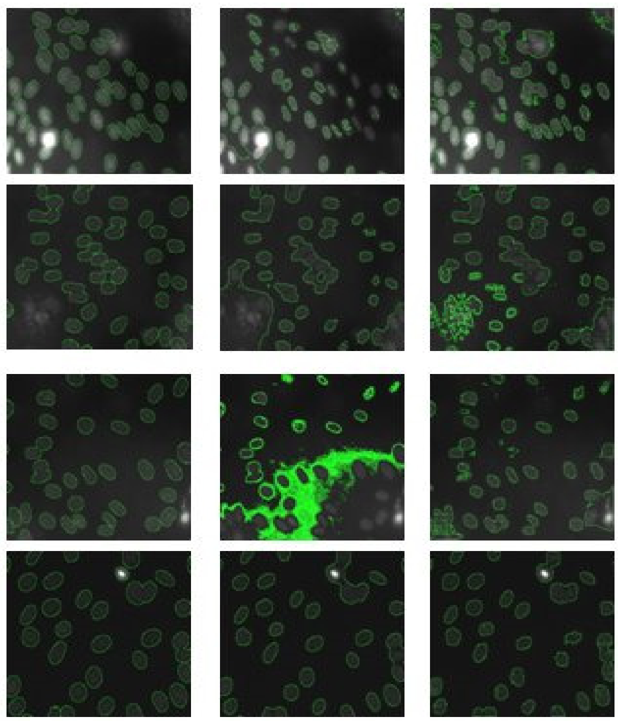

Figure 5: (a) Ground truth (b) Graph cut segmentation (c) Proposed model

The strength of the proposed model lies in its ability to provide an interactive segmentation platform for users (as observed in Figure 4) while carrying out graph cut segmentation on partitioned units. In terms of running time, the traditional graph cut segmentation has the least followed by proposed model; the geodesic active contour has the highest running time.

One shortfall of the proposed model is that it has high running time; this is due to the fact that graph cut segmentation is carried out sequentially amongst the partitioned units. In order to save time, the graph cut segmentation can be carried out in parallel in all partitioned units.

4. CONCLUSION

This research proposed a partitioned graph cut segmentation using an interactive approach with promising results. Improvements were observed over the traditional interactive graph cut segmentation model.

5. CONFLICT OF INTEREST

There is no conflict of interest associated with this work.

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