Automated Object Counting (Coins, Cells, etc.)

Project Report — Mid Semester (ECE501: Digital Image Processing)

NetraByte — Group Members

Aashi Shah (AU2340041) Bansi Mahkana (AU2340191)

Diya Patel (AU2340184) Nirjara Jain (AU2340010)

School of Engineering and Applied Science (SEAS)

Ahmedabad University

***Abstract*—Automatic object counting works to precisely identify and count multiple, usually similar, objects in digital images. This report introduces our initial progress on pre-processing, cell detection, and counting methods using traditional image processing. We describe a candidate set of object classes, pre-processing techniques, segmentation pipelines (including thresholding and morphological processing), and connected component analysis(for instance, contouring) for counting. Initial experiments on sample images show encouraging detection rates with traditional pipelines.**

***Index Terms*—Cell detection, segmentation pipelines, thresholding, morphological processing, contouring.**

I. Introduction

Counting near-identical or identical objects like cells in cell images in microscopy is an essential application in computer vision in the context of biomedical diagnostics and research. This project is aimed at designing an object counting system automatically based on the LIVECell dataset [1], which offers large-scale, label-free live cell imaging. The method employs conventional image processing methods like preprocessing, segmentation, and connected component analysis to precisely locate and enumerate individual cells while resolving issues such as overlapping objects, illumination change, and image noise.

II. Methodology

A. First approach: Otsu Thresholding without Morphological Processing

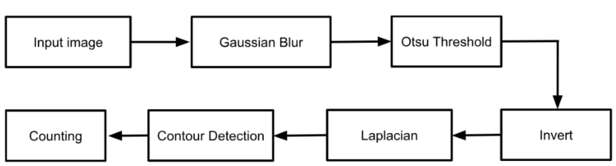

Fig. 1: Flowchart of Approach 1

1) Preprocessing: Images were converted to grayscale. Noise reduction was performed using Gaussian blurring with 5×5 kernel. Contrast enhancement and background smoothing were achieved.

2) Cell Detection:

- Global thresholding (Otsu's method): Automatically determined an optimal threshold separating the foreground (objects) from the background. The binary mask was inverted so that the objects appeared white.
- Laplacian edge enhancement: In the threshold-based approach, the Laplacian operator was used to sharpen object boundaries before contour extraction.

3) Post-processing and Counting:

- Small noise regions were removed based on area thresholding.
- Contours were extracted and filtered by area to retain only valid cells.
- Each detected contour was drawn on the image, and the total number of valid contours was used as the object count.

B. Second approach: Adaptive Thresholding with Morphological Processing

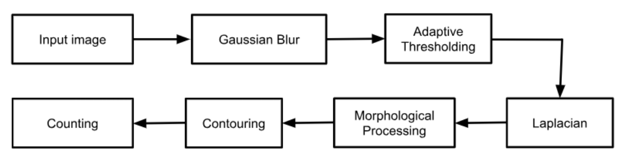

Fig. 2: Flowchart of Approach 2

1) Image Acquisition and Preprocessing: The noise in the grayscale images is minimized by a Gaussian blur with a size of (5×5) kernel.

2) Illumination Correction and Thresholding: Illumination is corrected by large-kernel Gaussian blur subtraction. The adaptive thresholding distinguishes the cells from the background.

3) Morphological Enhancement: The Laplacian filtering makes the boundaries sharp. Morphological transformations (the top hat, the closing, and the dilation) are tightening the mask and showing the distinct cell masks.

4) Counting: The connected components are identified by the function `cv2.findContours`. Each cell corresponds to an individual contour represented by a green border line.

These pipelines enable accurate and interpretable cell counting using traditional image-processing techniques without the need for deep learning models.

III. Preliminary Results

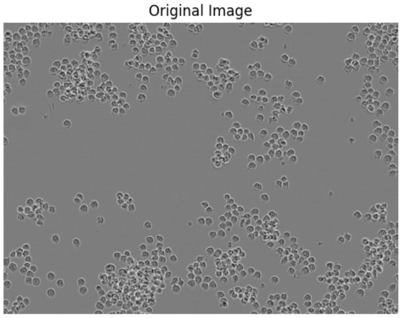

Fig. 3: Original Image

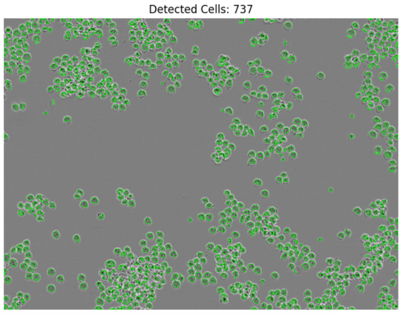

Fig. 4: From Approach 1

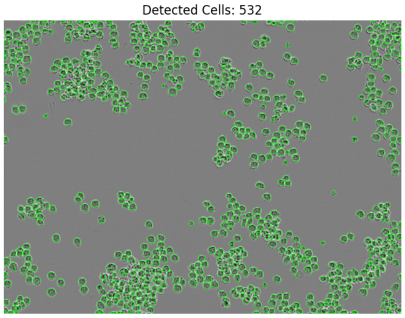

Fig. 5: From Approach 2

IV. Discussion

A. Approach 1: Otsu Thresholding

- It selects one brightness level to separate cells from the background.
- It is difficult to separate cells from the background with noisy or uneven images — overcounts cells.
- Works well when the lighting is even
- For the selected original image, it detected 737 cells, which means that it overcounted the cells.

B. Approach 2: Adaptive Thresholding

- It computes the threshold locally for different regions of the image.
- It performs better for uneven illumination and contrast compared to global methods.
- It minimizes false positives and enhances the segmentation of cell groups.
- For the same original image, it identified 532 cells, providing a more realistic count.

C. Challenges faced:

- We were unable to convert all .json ground truth annotation files to .tiff; only one image worked.
- We intended to use a strict Laplacian of Gaussian filter, but then changed to a Gaussian $\longrightarrow$ Thresholding $\longrightarrow$ Laplacian for better results.

V. Conclusion

- This project implements the automated cell detection and counting using the traditional image processing techniques on LIVECell dataset.
- We used the preprocessing step, which is Gaussian blur, and the morphological operations, which enhanced segmentation and reduced noise.
- Both Otsu's and Adaptive Thresholding methods were tested — Adaptive Thresholding provided more consistent results in comparison to Otsu Thresholding.
- In spite of obstacles such as poor contrast and overlapping cells, the pipeline worked routinely and was interpretable without deep learning-based methods.
- The framework outlines that classical methods remain efficient, transparent, and suitable for biomedical image analysis with a scope for future enhancement using hybrid or learning-based techniques.

VI. Next Steps

Next Set of Work:

- Currently, we are working on only 1 type of cell (out of 8 types). We plan to create a model that will be trained and evaluated on the entire dataset.
- The ground truth/annotations of our dataset are present in JSON file format. We have yet to develop a pipeline for converting JSON to images.
- In the future, we will compare our segmented output to the provided ground truth/annotations for calculating the accuracy.

Acknowledgment

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References

[1] C. Edlund, T. R. Jackson, N. Khalid, N. Bevan, T. Dale, A. Dengel, S. Ahmed, J. Trygg, and R. Sjögren, "LIVECell—A large-scale dataset for label-free live cell segmentation," *Nature Methods*, vol. 18, no. 9, pp. 1038–1045, 2021. [Online]. Available: https://www.nature.com/articles/s41592-021-01249-6

[2] N. Senthilkumaran and S. Vaithegi, "Image segmentation by using thresholding techniques for medical images," *Computer Science & Engineering: An International Journal*, vol. 6, no. 1, pp. 1–13, 2016. [Online]. Available: Research_Paper_Link