CS231n Progress report

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Abstract

Cell counting is a laboriously difficult task that would greatly benefit from automation. In this paper, we attempt to describe our progress in the automatic segmentation and counting of cells given an image.

1. Introduction

We are currently attempting to automate the tedious process of counting cells. To that end, we started by downloading the BBBC005 dataset from the Broad Institute https://data.broadinstitute.org/bbbc/BBBC005/. The dataset was initially in the Tag Image File Format (TIFF), but images were converted to JPEG for better integration with existing code bases. The dataset includes 1200 labeled high quality in-focus images in the dataset. For each of these 1200 images, we are given both a cell count and a second image where the foreground has been identified. We use about 100 of those for fast prototyping with the eventual aim of using a standard 80-20 train/test split. The results of our models will be evaluated using a simple classifier loss such as SVM or Softmax.

2. Technical Approach

2.1. Initial Approach

In our initial approach, we attempted to use the Mask-RCNN network on our dataset. However, this method was not feasible because the Mask-RCNN approach requires identification of regions of interest within our training data. This would require creating bounding boxes for each cell in our training images. While doable, it is arguably the problem we are trying to solve/automate and is not immediately available in the Broad Institutes dataset. We will continue to investigate how we can get around this technical issue of using Mask-RCNN network for our problem. Principally, we are interested in Facebook AI Researchs Feature Pyramid Network (FPN) approach to identify objects in images, a major component to Mask-RCNNs reported success.

2.2. New Approach

To circumvent the technical issues in our initial approach, we have been experimenting with a new approach to solve the cell counting problem. The approach requires a two step solution.

- Train a Cycle-GAN or FPN to detect the foreground from the background.
- Use a CNN to predict cell counts from the output from the Cycle-GAN or FPN.

Cylce-GANs are a recent advance in CNN literature which allow for image to image translations with cycle consistent losses. In simpler words, they allow a user to turn a horse into a zebra and back into a horse, making sure that the second horse is similar to the first one. We believe a similar technique can be used to turn images of cells into images of outlines of cells. The outlines of cells can then be used to count the number of cells within a picture (Figure 1).

We decided to break up the learning task into two different tasks because we believe it is a simpler problem compared to end-to-end learning. Furthermore, it allows us to decompose problem in training as either problems on the GAN/FPN side or the CNN side. An appealing approach with our method is that the model is now agnostic to how the cell images were captured. The GAN/FPN will handle the foreground detection while the CNN will handle the counting. In our current dataset, the cell counts go from 1-100 which can easily framed as a classification task. An alternative approach might be to predict counts from the density of cells which will make our model more applicable to newer datasets. Training for either of these tasks (e.g. classification or regression) with our model would only require minimal modification to the final FC layers and could even benefit from using transfer learning.

3. Initial results

We have done some preliminary training on the Cycle-GAN side to see if its possible to to foreground detection

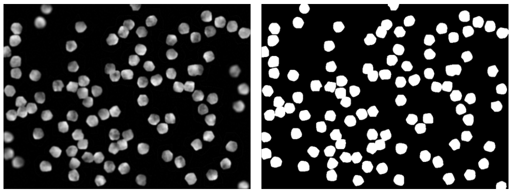

Figure 1. Sample images for a well focused training example from the training dataset. The image on the right is the camera output. The image on the left is the labeled foreground. The cell count is given at 100. The first step in our pipeline requires translating images from the left to the right using a cycle-GAN. The next step requires using the generated images as input into a CNN capable of counting cells.

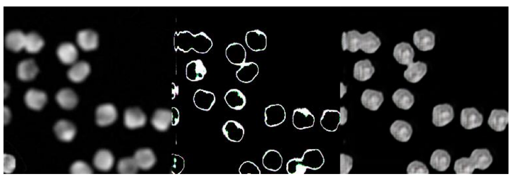

Figure 2. initial results for the Cycle-GAN. The image on the left represents the starting image. The image in the middle is the foreground separation from the background while the image on the right is the inverse transformation. In our next step, we will use the output in the middle panel as input into a second network to count the number of cells or to estimate the cell density. The lower panels are a second example.

using cycle-GANs. The results are shown in Figure 2. The cycle-GANs are learning to identify the outlines of cells (middle panels) though more experimentation is definitely needed.
We have also worked towards implementing an FPN and have done some preliminary training with this model as well. The results are shown in Figure 3. The FPN seems to learn a low resolution mask over the cells, which could also be useful for predicting counts via density.

4. Next steps & Timeline

Over the next three weeks, we will optimize the cycle-GAN/FPN to identify the foreground in our dataset. We will then use this model to feed into a CNN for predicting cell counts. Our projected timeline is below:

- May 16th-May 23rd: Optimize Cycle-GAN/FPN results for better foreground detection.
- May 24th -May 31st: Experiment with various CNN architectures to see which ones perform better.
- June 1st-June 4th: Write paper/ finish experiments.

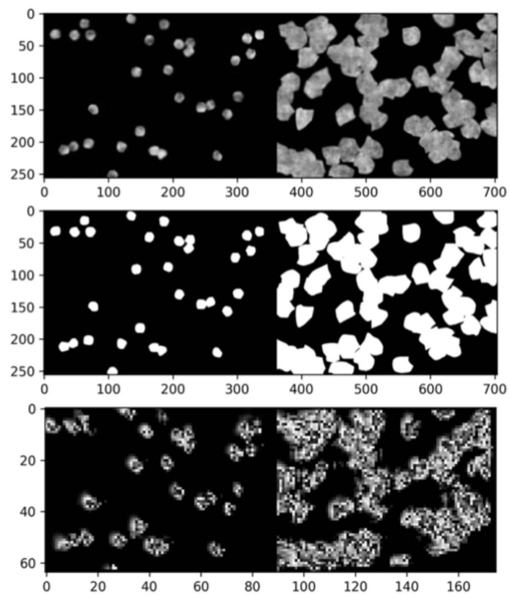

Figure 3. Initial results from the FPN after 100 epochs. Top row shows two examples of typical cell microscopy images from the Broad Institute dataset. The middle row is their corresponding foreground mask. The bottom row is the output of our FPN model after 100 epochs, which attempts to generate a low-resolution foreground mask for a given image.