description of illustrative embodiments that proceeds with reference to the accompanying drawings.

BRIEF DESCRIPTION OF THE DRAWINGS

[0011] The foregoing and other aspects of the present invention are best understood from the following detailed description when read in connection with the accompanying drawings. For the purpose of illustrating the invention, there is shown in the drawings embodiments that are presently preferred, it being understood, however, that the invention is not limited to the specific instrumentalities disclosed. Included in the drawings are the following Figures:

[0012] FIG. **1** shows an example DHM setup;

[0013] FIG. **2** illustrates example cell images with different quality;

[0014] FIG. **3** shows the system diagram illustrating the actors and operations used to assess image quality, according to some embodiments;

[0015] FIG. **4** illustrates a technique for extracting the cells, according to some embodiments;

[0016] FIG. **5**A illustrates a first example extraction of cells;

[0017] FIG. **5**B illustrates a second example extraction of cells;

[0018] FIG. **6**A illustrates an example of the multi-layer architecture that may be employed by the CNN, according to some embodiments;

[0019] FIG. **6**B provides an alternate view of the multi-layer architecture shown in FIG. **6**A;

[0020] FIG. **7** shows an assessment of classification accuracy of the techniques described herein, according to one example implementation;

[0021] FIG. **8** provides an example deployment of a trained CNN, according to some embodiments; and

[0022] FIG. **9** provides an example of a parallel processing memory architecture that may be utilized by image processing system, according to some embodiments of the present invention.

DETAILED DESCRIPTION

[0023] The following disclosure describes the present invention according to several embodiments directed at methods, systems, and apparatuses related to identifying the quality of the cell images acquired with digital holographic microscopy (DHM) or another type of microscopy device using convolutional neural networks (CNNs). More specifically, techniques are described herein for differentiation between "good quality" cell images where the cells are captured in focus and the "poor quality" images that are out of focus. In some embodiments, the problem is formulated as a binary image classification problem where the two classes are in-focus/out-of-focus. This problem is then solved using a CNN. As explained in further detail below, this general framework can be expanded upon with various enhancements, refinements, and other modifications in different embodiments of the present invention.

[0024] FIG. **3** shows the system diagram illustrating the actors and operations used to assess image quality, according to some embodiments. Briefly, a Microscopy Device **305** is used to acquire one or more Microscopy Images **310**. The Microscopy Device **305** may be any system known in the art capable of acquiring microscopy images of cells. For example, in some embodiments, the Microscopy Images **310** may be acquired using off-axis digital holographic microscope (DHM). The acquisition can alternatively be done using other DHM techniques such as on axis configurations. In other embodiments the Microscopy Device **305** uses other cell imaging techniques known in the art which can be used to acquire the Microscopy Images **310**. Example alternative imaging techniques include, without limitation, bright field microscopy, dark field microscopy, differential interference contrast, fluorescence microscopy, confocal microscopy, two-photon excitation microscopy, and multiphoton microscopy.

[0025] Because the acquisition of the Microscopy Images **310** is a tedious procedure due to the need to prepare the blood samples, in some embodiments techniques such as Deep Convolutional General Adversarial Networks (DCGAN) may be used to generate synthetic data at different foci. As would be generally understood by one skilled in the art, generative models model the distribution of individual classes. Generative adversarial networks (GANs) generally represent a class of artificial intelligence algorithms that falls under the category of "unsupervised learning." In its simplest form, GANs are a combination of two neural networks: one network is learning how to generate examples (e.g., synthetic DHM images) from a training data set (e.g., images acquired using Microscopy Device **305**), and another network attempts to distinguish between the generated examples and the training data set. The training process is successful if the generative network produces examples which converge with the actual data such that the discrimination network cannot consistently distinguish between the two.

[0026] Continuing with reference to FIG. **3**, the Microscopy Images **310** are received by an Image Processing System **345** that has processing resources for training a CNN **330** based using the Microscopy Images **310**. Before training the CNN **330**, a Preprocessing Module **315** extracts the independent cells from the Microscopy Images **310** for training. Each cell is extracted as a Set of Pixels **320**. For the purposes of this disclosure, each individual Set of Pixels **320** is also sometimes referred to as a "cell image." It should be noted that various types of image classification models can be used as an alternative to CNNs in other embodiments including, without limitation, linear classifiers (e.g., logistic regression, naïve bayes classifiers, etc.), kernel estimation k-means clustering, nearest neighbor classification, support vector machines, decision trees, boosted trees, random forests, and different configurations of neural networks.

[0027] FIG. **3** shows the system diagram illustrating the actors and operations used to assess image quality, according to some embodiments. FIG. **4** illustrates a technique **400** for extracting the cells, according to some embodiments. For this example, assume that the acquired images have a dimension of 384×512 and 100 images are acquired per second. To perform background correction the average of the first 100 images is computed at step **405** and the average image is subtracted from each acquired image at step **410**. Next, at step **415**, adaptive thresholding is applied to capture all the bright components in the image. Various adaptive thresholding techniques generally known in the art may be applied at step **415**. For example, in one embodiment, the intensity values of the local neighborhood of each pixel are used to determine a threshold for the pixel. If the pixel is below the threshold value, it is set to some minimum value (e.g., pure black). After thresholding, one or more exclusion