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Tracking of Fluorescent Cells Based on the Wavelet Otsu Model

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Abstract-The mainstay of the project is to demonstrate that the proposed tracking scheme is more accurate and significantly faster than the other state-of-the-art tracking by model evolution approaches.The model is validated by comparing it to the original algorithm.The proposed tracking scheme involves two steps. First, coherence-enhancing diffusion filtering is applied on each frame to reduce the amount of noise and enhance flow-like structures. Second, the image segmentation is done by the Wavelet OTSU method in the fast level set-like and graph cut frameworks. This model evolution approach has also been extended to deal with many cells concurrently. The potential of the proposed tracking scheme and the advantages and disadvantages of both frameworks are demonstrated on 2-D and 3-D time-lapse series of mouse carcinoma cells.

Key words*-enhancing diffusion filtering, Wavelet OTSU, image segmentation, time-lapse series of mousecarcinoma cells.*

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I. Introduction

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The system require cell tracking to be fast, affordable and, most importantly, precise and robust. Segmentation of the cells is important for allowing different regions of the body to develop differentially for different uses. The process of detecting and tracking biological features such as cancerous cell growth and nuclei is complicated by the fact that they constantly change their shape. Shape changes happen both continuously as the biological features grow and discontinuously as they divide or die. This can be done effectively if they are fluorescent. So fluorescence microscopy technique has to be used for segmenting and tracking of cells. The extraction of fluorescence time course data is a major bottleneck in high-throughput live-cell microscopy. An extendible framework is based on the open-source image analysis, which aims in particular at analyzing the expression of fluorescent reporters through cell divisions. The ability to track individual cell lineages is essential for the analysis of gene regulatory factors involved in the control of cell fate and identity decisions.

II. Existing System

Cells are detected based on intensity, texture, or gradient features. Detected cells are associated between two or more consecutive frames. A manual separation of cells clustered in the first frame is required to track each of them correctly over time. This complicates the use of the tracking scheme in experiments with high density of tightly packed cells. Choice of the filtering technique used in existing system has a tracking scheme significantly slower for high-throughput applications. Integration of the FLS framework with a different approximation of the mean curvature motion to obtain smoother function directly to the Kohli–Torr algorithm affects the overall speed of the GC framework. Cell segmentation and tracking in time-lapse fluorescence microscopy images is a task of fundamental importance in many biological studies on cell migration and proliferation which was used in this. The segmentation and tracking accuracy, robustness, and computational cost was been calculated using different algorithms.

III. Proposed System

The proposed system involves segmentation and shape tracking of mouse carcinoma cells. The process of the tracking scheme includes coherence enhancement diffusion filtering and morphological operations where the cells are being filtered to remove the distortion and with the help of the morphological operations enhancement of features is done. Then the segmentation technique is followed where the cell boundaries are being tracked and the growth of the cells are detected.

CONVERSION OF IMAGE

The aim of conversion of image is to do an improvement in the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis task. Image pre-processing is used to convert the image and it uses the redundancy in images. Neighboring pixels corresponding to one real object have the same or similar brightness value. This process produces a corrected image that is as close as possible, both geometrically and radio metrically, to the radiant energy characteristics of the original scene. Radiometric and geometric are the most common types of errors encountered in remotely sensed imagery. In this project the conversion is

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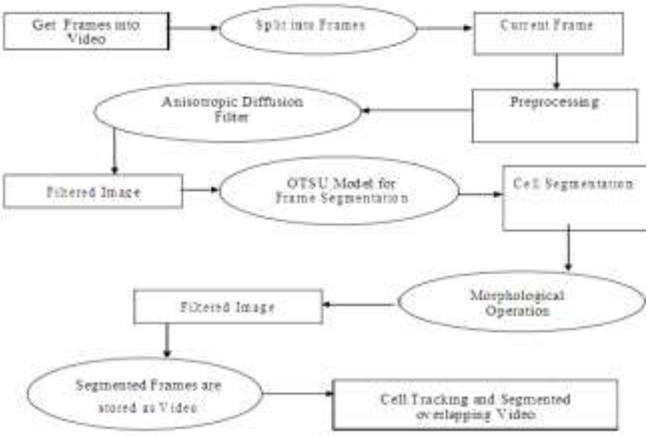
done to convert the color image into gray scale using mat lab software.

IMAGE AND VIDEO HISTOGRAM ANALYSIS

An image histogram is a type of histogram that acts as a graphical representation of the tonal distribution in a digital image. It plots the number of pixels for each tonal value. By looking at the histogram for a specific image a viewer will be able to judge the entire tonal distribution at a glance. Image histograms are present on many modern digital cameras. Photographers can use them as an aid to show the distribution of tones captured, and whether image detail has been lost to blown-out highlights or blacked-out shadows. The horizontal axis of the graph represents the tonal variations, while the vertical axis represents the number of pixels in that particular tone. The left side of the horizontal axis represents the black and dark areas, the middle represents medium grey and the right hand side represents light and pure white areas. The vertical axis represents the size of the area that is captured in each one of these zones. Thus, the histogram for a very dark image will have the majority of its data points on the left side and center of the graph. Conversely, the histogram for a very bright image with few dark areas and/or shadows will have most of its data points on the right side and center of the graph.

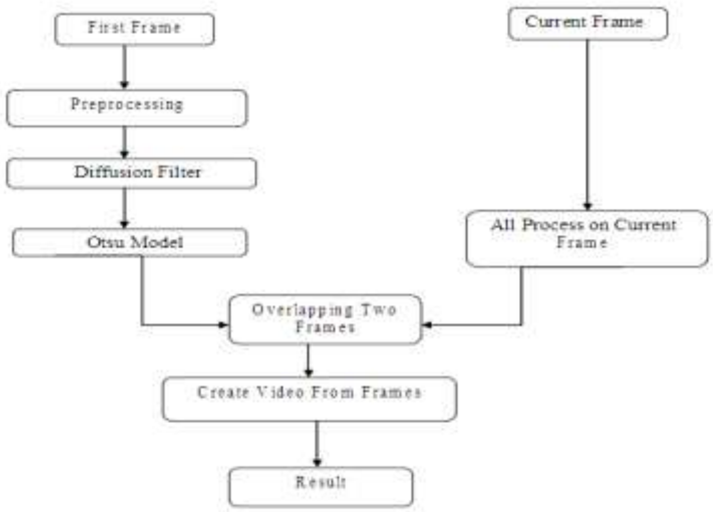
OTSU MODEL

In computer vision and image processing, Otsu's method is used to automatically perform clustering-based image thresholding or the reduction of a gray level image to a binary image. The algorithm assumes that the image contains two classes of pixels following bi-modal histogram i.e. foreground pixels and background pixels, it then calculates the optimum threshold separating the two classes so that their combined spread i.e. intra-class variance is minimal.



IV. WORK FLOW DIAGRAM

The work flow of the proposed system is been divided in three modules. First module is used to find out the input time lapse series for the images entering i.e. the cell structured image. These are then undergone through second module where the process of coherence-enhancing diffusion filtering is done where the images are being filtered and divided into two segments. One is captured entering cells and clustering cells. This process is being continued until the entire images are filtered.For captured entering cells are then under gone with the process of Otsu model integrated with object indication function and deals with overlapping cells. For clustering image Otsu model without any topological constraints are being considered and discard small components.



V. K-MEANS CLUSTERING METHOD

Vector quantization, originally from signal for clusteranalysis in datamining. k-means partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells. The problem is computationally difficult (NP-k-meansclustering is a method hard);however, there are efficient heuristic algorithms that are commonly employed and converge quickly to a local optimum. These are usually similar to the expectation maximizationalgorithm for mixtures of Gaussiandistributions via an iterative refinement approach employed by both algorithms. Additionally, they both use cluster centers to model the data; however, k-means clustering tends to find clusters of comparable spatial extent, while the expectation-maximization mechanism allows clusters to have different shapes.

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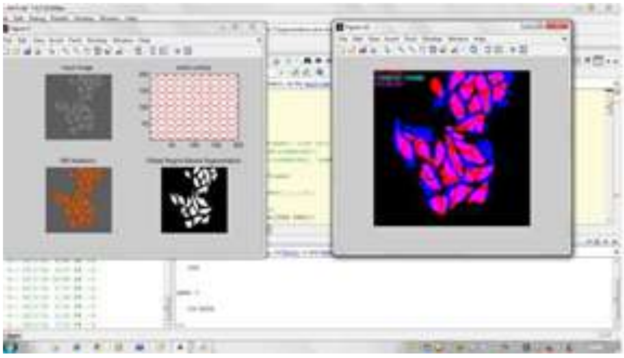
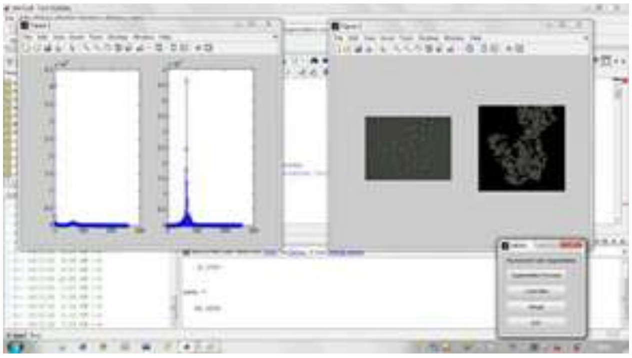
VI. RESULTS





VII. COMPARISON DESCRIPTION.

The Mean Square Error (MSE) and the Peak Signal to Noise Ratio(PSNR) are the two error metrics used to compare image compression quality. The MSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error.If the value of PSNR is high which means good quality and if it is low bad quality. PSNR is using a term mean square error (MSE) in the denominator. So, low the error, high will be the PSNR.

Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) are used to comparing the squared error between the original image and the reconstructed image. There is an inverse relationship between PSNR and MSE. So higher PSNR value indicates the higher quality of the image.

Therefore the OTSU model has PSNR value of 55.6574 and MSE of 0.1767 whereas on the contrary the Chan-Vese model has PSNR value of 24.0654 and MSE of 255.This tells us that the proposed OTSU model is more efficient than that of the original algorithm.

VIII. LITERATURE SURVEY

De convolution is an operation that mitigates the distortion created by the microscope[10]. This paper presents an overview of various deconvolution techniques of 3D fluorescence microscopy images. It describes the subject of image deconvolution for 3D fluorescence microscopy images and provides an overview of the distortion issues in different areas. A brief schematic description of fluorescence microscope systems and provides a summary of the microscope point-spread function (PSF), which often creates the most severe distortion in the acquired 3D image. It discusses the ongoing research work in the area and provides a brief review of performance measures of 3D deconvolution microscopy techniques. It also provides a summary of the numerical results using simulated data and presents the results obtained from the real data**.**

IX. CONCLUSION

Image segmentation plays an important role in image analysis and computer vision system. Among all segmentation techniques, the automatic thresholding methods are widely used because of the advantages of simple implementation and time saving. OTSU method is one of the thresholding methods and frequently used in various fields. Experimental results show that the proposed system performs better than the chan-vese segmentation method for mouse carcinoma cell samples.

In Image processing OTSU's method is used to automatically perform clustering- based image thresholding, or the reduction of a gray level image to a binary image. Otsu's thresholding method involves iterating through all thepossible threshold values and calculating a measure of spread for the pixel levels each side of the threshold, i.e. the pixels that either fall in foreground or background. The algorithm assumes that the image contains two classes of pixelsfollowing bi-modal histogram (foreground pixels and background pixels) ,it then calculates the optimum threshold separating the two classes so that their combined spread (intra-class variance) is minimal.

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