Multiple tracking of objects in cell colony at video sequence

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Abstract – **In this paper we present a system of biological cell colony tracking exploiting modified adaptive background subtraction algorithm. Presented algorithm allows segmenting movable objects at video sequence comprising several noises specified quality of tools. Numeric parameters of segmented objects are estimated on the base of the algorithm; specific parameters make it possible to cluster the objects.**

Keywords: image processing, foreground segmentation, background subtraction

I. INTRODUCTION

Diseases affecting tissue cells can be identified either as changing cell morphology by cytological analyses or abnormal motility of affected cells. Changes in cell morphology and dynamic adjectives may be as the true indicator of disease. A cell trajectory, its speed, acceleration, and a cell division rate (mitosis) can provide essential contribution to following cell pathology diagnostics [1].

Moving object detection is a crucial part of automatic video surveillance systems. There are many approaches purposed for this task. One of the most common and effective approach to localize moving objects is background subtraction, which uses normal distribution. The sequence of bitmapped images is used in this approach. All images have equal size; we suppose that pixel intensity changes with next frame. In practice video sequence has noises so frames make random process for every pixel. In many cases distribution of noise is considered as normal. So process in pixel is considered as normal too. Estimation of mathematical expectation (mean value) and standard deviation of process are calculated as appropriate functions of pixel intensity value on previous frames. If intensity deviation of previous mean does not exceed specified threshold then pixel is attributed to foreground else to background. But in many cases using single process for every pixel is useless because usually video sequence includes dynamic background objects such as shadows cast by moving object, illuminations changes, and camouflage. To avoid this background subtraction method using mixture of normal distributions are implemented [2], [3].

II. OBJECT SEGMENTATION

Image preprocessing often is implemented before object segmentation for image filtering and improvement of image quality. But in our research this step was absent because image preprocessing makes object tracking worse because of it is gives more blur of picture.

Pixel-based background subtraction techniques are among the most important and widely used tools in video analysis. It involves a class of change detection algorithms in which a per-pixel statistical model is estimated for the background. This background model is then used to classify the incoming video stream's pixels as foreground or background. Only the foreground pixels are retained, thus providing a change image which can be used for various kinds of object detection, classification, and tracking purposes.

Objects are segmented by modified algorithm based on background subtraction method using mixture of normal distributions described in [2], [3], [4]. Initial data from the Institute of genetics and cytology is a video frames obtained by a stationary camera integrated in a microscope. Acquisition of images was carried out periodically every 30 minutes over the time of 2-3 weeks. By this reason original video film contains little number of frames. Initially commonly used background subtraction algorithm exploits several first frames of video sequence that are eliminated from further consideration.

The presented method does not exclude these first frames from the analysis. Previously movable objects are separated from the background on the base of constructed frame pattern (creating several Gaussian distributions for every pixels based on this initial information from several first frames), and then moving objects are segmented for all succeeded frames. We used a dynamic background subtraction method at least that has five or more distributions for more effective segmentation. Every new Gaussian distribution has initial average mathematical expectation and standard deviation because we can not set these mathematical parameters to zero.

In the beginning every frame of video sequence is converted to gray-color picture because foreground and background not differ from other by color in RGB palette. Due to imperfect object illumination usual videos have undesirable abnormalities such as flickering (changing of natural sun intensity over a day). It is assuming that a background is static (iterative) so the intensity of a background is static (iterative) as well. To avoid illumination problems on the preprocessing stage our algorithm normalizes a frame taking into account average intensity of the previous frames.

A fixed pixel on a frame is characterized by three colors, or intensity for grayscale image. Changing of these parameters is described by processes. Accordingly, each pixel is associated with three processes or single process. In our research we use only single process for a pixel at one frame. A process is represented by mathematical parameters of a pixel. A process means changing these parameters; they depend only on parameters on the previous stage. Calculating of mathematical expectation and standard deviation of previous pixel process depends on external parameters (formula 1) [2], [3], [4]:

$$m_t = (1-\alpha_1)m_{t-1} + \alpha_1 x; \quad \sigma^2 = (1-\alpha_2)\sigma_{t-1}^2 + \alpha_2 (x - m_t)^2 , \quad (1)$$

where α_1, α_2 - determined by researcher parameters, t - number of frame in video sequence, x - color of current pixel.

Thereafter single or multiple Gaussian filters with 5 x 5 pixels kernel are used to avoid residual noises and static threshold classification is applied again. This size of kernel was chosen in consideration that video sequence has not objects (cells) smaller than 5 x 5 pixels. And then threshold classification relative to specified threshold T (formula 2) is applied again to convert the image to binary format [5]:

$$T = \frac{m_1 + m_2}{2} + \frac{\sigma^2}{m_1 + m_2} ln\left(\frac{P_1}{P_2}\right), \qquad (2)$$

where m_1 and m_2 – mean values of intensity of background and foreground; σ – mean square deviation of background and foreground ($\sigma = \sigma_1 = \sigma_2$); P_1 и P_2 – a priori probability of background and foreground.

III. OBJECT TRACKING

The level of noise of the images under consideration is very high; therefore, on preprocessing stage filtering and normalizing algorithms are exploited. Gaussian filter is proved to be rather effective; nevertheless, filtering is not capable to eliminate all contaminations and defects of video filming. So, for cleaning frames a heuristic dynamic procedure is applied; that is if a cell becomes immovable and time of it living exceeds prescribed threshold, it is considered as dead cell and is excluded from a list of objects under monitoring.

Above all, we assume our objects in nature cannot jump (discrete moving). A simple tracking algorithm based on selection the nearest similar object on the subsequent frame and the statistical Mahalanobis distance with equal parameters is proposed in this paper [6]. Besides, it is supposed cells cannot superpose, that is cells are moving only on two-dimensional plane.

Morphological attributes of an object are eliminated from the method, because cells are subject to change their shapes, size, and texture. Mitosis (cell division) and necrosis (cell death) are inherent essential functions of a cell.

A size of a region of interest (Mahalanobis distance) which is used for a search of next position of current cell under monitoring is fixed for all cells. It is specified in compliance to an average diameter of cells and maximal distance that overcome single cell at time between two frames of video sequence.

If there are several objects in the region of the interest, then direction of motion is exploited. In fact, in this case information on previous frames is applied. There is a special case when a new object appears on the frame. Such situation occurs on cell dividing, separating of a cell from compact group of cells, returning of a cell to an area caught by video camera. If the object is recognized as a cell, it is marked as a new one and is included to a list of objects.

Tracking of objects yields background for further their classification. Objects are classified on terms of their rate of motion, acceleration, navigation, and changing of direction. In certain cases this information is reliable base for following recognition of abnormal cells from normal cells.

IV. OBJECT CLASSIFICATION

K-means algorithm is used for object classification [7] because it requires little computational power. Moreover, cell classification uses 4 clusters: good cells, diseased cells, dead cells (not moving objects) and additional group when cell are not attributed to first clusters, for example objects with very small speed.

Object classification is executed on basic of following measures:

– speed;
– direction;
– time of it living.

First random objects are selected for classification. When classification executes big number of clusters appears the number of that maybe is being more than four.

Most big clusters are choused from all clusters and are marked as first three clusters: good cells, diseased cells, dead cells. Last clusters are deleted from consideration.

We suppose that diseased cells have big speed of moving, big angle of deviation from linear moving. So cluster is choused that has these objects Then cluster that has objects with smallest time of living is choused.

Weights of measures are needed for correct classification. Main measure for object classification is objects speed then is direction of moving. The time of living has smallest weight because this parameter depends on quality of initial data and effectiveness of implemented methods.

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