Image Analysis and Processing of Skin Cell Injury Based on OpenCV

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Abstract. OpenCV is an open source computer vision and machine learning software library that provides a common infrastructure for computer vision applications and accelerates their use of machine awareness in commercial products[1]. This paper uses the visual processing algorithm provided by OpenCV to analyze and process the image of skin cells in detail, and quantitatively determine the percentage of damaged cells in the image. First, dilation, opening operation, closing operation, coarsening, refinement, skeleton, tailoring, boundary extraction, holes filling, connected components and so on of a variety of morphological methods are used in the process of corrosion for the graphics pretreatment. Then the watershed algorithm is adopted to image segmentation. This paper expounds the ridge algorithm to water in detail. Finally, in order to determine the proportion of damaged cells in the segmented cells, the polygonal fitting method in graphic image processing was creatively used, and the polygonal fitting method was described in detail, which successfully solved the task of the research topic.

1. Introduction

Digital image processing methods stems from two main application fields: (1) Improving graphic information for people to interpret; (2) Image data is processed for storage, transmission, and presentation for automatic machine understanding. Image segmentation is one of the most important basic links in the field of pattern recognition, image understanding and computer vision. With the development of mathematical theory especially the theory of applied mathematics, people with the new mathematics theory, make a deep research on image segmentation problem, and put forward many methods of image segmentation[2]. The microscopic skin tissue damage can also process through the cell image segmentation method. Image segmentation is the technical process of dividing an image into several specific and unique regions and extracting the interested objects. It is one of the most fundamental and important fields in the field of image processing and computer vision and the basic premise of image analysis and image recognition. However, there are still many difficulties in segmentation. One of the reasons is that although people have done a lot of research work on image segmentation, since there is no general segmentation theory, most of the segmentation algorithms proposed are targeted at specific problems, and there is no general segmentation algorithm suitable for all images. The second reason is that there is no standard method to select a suitable segmentation algorithm for a given actual image segmentation problem[3]. This paper uses a variety of mathematical morphology method to extract the target from background area cell, uses the minimum distance
transformation algorithm, image normalization, and times region of interest (ROI) gradient image dot to suppress useless gradient information, then uses the improved control mark watershed segmentation algorithm of cell adhesion to restore the original boundary of adhesion cells, effectively achieving adhesion cell division[4].

On this basis, the polygonal fitting method of image edge was creatively applied to detecting the difference between normal cells and damaged cells, and the proportion of damaged cells in the microscopic image of cells was successfully obtained, providing a scientific basis for targeted treatment of skin.

2. Material and Methods

Through careful observation of the original image, it is found that the image has degradation phenomenon, so the image restoration is required. The purpose of image restoration is to improve the image with predetermined targets and eliminate the noise caused by sensors, digital converters and display degradation. Image restoration is mostly an objective process, and the restoration technology is oriented to the degradation model. Both spatial filtering in restoration and frequency-domain filtering involve smoothing and sharpening techniques [3]. High pass filtering and threshold method are selected to enhance the image in this paper. The reason for using high pass filtering is to enhance cellular ridges while reducing contamination effects. Ridge enhancement is accomplished using the fact that the ridge contains high frequencies, while high pass filtering does not alter high frequencies. On the other hand, the filter reduces the low-frequency component, which corresponds to the slow-varying grayscale of the image, such as background and pollution. In this way, enhancement can be achieved by reducing all features except high frequency, in which case high frequency is of interest. The main purpose of threshold processing is to avoid the loss of grayscale tone after high-pass filtering, to lighten the tone as the mainstream, and to enhance the details of interest.

Figure 1(a) shows the original image, and Figure 1(b) shows its histogram. It can be seen that the image has a low contrast. Generally speaking, the low-contrast image has a narrow histogram and is concentrated in the middle of the grayscale image. In the analysis of the original image, we can see that the components of the histogram are mainly concentrated in the center right of the grayscale value in the grayscale image, and the values are approximately concentrated between 90 and 230. For a monochrome image, this means that it is dark, as if the grayscale has been diluted.

Histogram equalization is to adjust the gray order distribution of the image, so that the distribution on the 0–255 gray order is more balanced, improve the contrast of the image, to improve the subjective visual effect of the image. Low contrast images are suitable for histogram equalization to enhance image details [5]. The image results after histogram equalization are shown in Figure 2(a). It can be seen that the histogram components in high-contrast images cover a wide range of grayscale levels, and the distribution of pixels is not uneven. Therefore, we conclude that if the pixels of an image tend to occupy the entire possible gray level and are evenly distributed, the image will have a high-contrast appearance and show a large change in gray tone. Figure 2(b) is a histogram of Figure 2(a).
Mathematical morphology is used as a tool to extract useful image components to express and depict regional shapes from images, such as boundary, skeleton and convex shell. The usual morphological image processing uses corrosion, expansion, open operation, closed operation, coarsening, refinement, skeleton, cutting, boundary extraction, hole filling, connected components and other operations.

Fig.2 (a) Histogram equalization of the original image. (b) Histogram. Corrosion and expansion are the basis of morphological treatment. In terms of expansion, A and B are the sets of $\mathbb{Z}^2$. The expansion of B on A in expressing $A \oplus B$ is defined as:

$$A \oplus B = \{ z | (B_{e})_{z} \cap A \neq \emptyset \}$$  \hspace{1cm} (1)

This formula is based on the mapping of B to its origin and the translation of the image by z. The expansion of B on A is the set of all the displacements of z. So B and A at least one element is overlap. According to this interpretation, equation (1) can be equivalently written as:

$$A \oplus B = \{ z | [(B_{e})_{z} \cap A] \subseteq A \}$$  \hspace{1cm} (2)

Fig.3 (a) Expansion operation. (b) Corrosion operation.

Let's say that B is a structural element, and A is an expanded set (Image objects). When structural element B is considered as a convolution template, Equation (2) has significant advantages over other definitions, which are more intuitive. B flips (rotates) about its origin, and then moves gradually across the set A (image). However, it is important to remember that expansion is based on set operations, so expansion is a non-linear operation, while convolution is a linear operation. Unlike corrosion, expansion is an object that "grows" or "coarsens" binary images. Figure 3(a) shows the results of the expansion operation of the skin cell image in this project.

In terms of corrosion, as set A and B in the $\mathbb{Z}^2$, the corrosion of B on A in expressing $A \Theta B$ is defined as:

$$A \Theta B = \{ z | (B_{e})_{z} \subseteq A \}$$  \hspace{1cm} (3)

The above formula indicates that the corrosion of B on A is a set of all the points z that B contained in A is shifted by z. Assuming that B is a structural element, since B must be included in A, this
statement is equivalent to that B does not share any common elements with the background. Therefore, corrosion can be expressed in the following equivalent form:

$$A \Theta B = \{z|(B)^c \cap A^c = \emptyset\}$$  \hspace{1cm} (4)

$A^c$ is $A$ complement, $\emptyset$ is an empty set.

Corrosion is a contraction or refinement operation. Figure 3(b) shows the corrosion operation results of skin cell images in this project.

In order to remove the small white areas in Figure 3(b), the region growth method can be used. This principle is very simple, according to the specific situation of their own images, set a regional area threshold (the threshold set in this project is 500), can be filtered. Figure 4(a) is the effect of removing the small white areas in Figure 3(b).

A hole is defined as a background area surrounded by a boundary connected by foreground pixels. In fact, hole filling can be achieved by algorithms based on set expansion, complement and intersection. For example, let A represent a set whose elements are 4 connected boundaries, each of which surrounds a background region (that is, a hole). Given a point in each hole, the goal is to fill all the holes with 1. In addition to the point at which each hole corresponds to a given position in $X_0$, which we have set to 1, we start by forming an array of 0's, $X_0$ (which is the same size as the array containing A). Then, fill all the holes with 1 as follows:

$$X_k = (X_{k-1} \oplus B) \cap A^c \hspace{1cm} k=1,2,3,\ldots$$

Where B is the symmetric element structure. If $X_k = X_{k-1}$ the algorithm ends at step k of the iteration. The set $X_k$ then contains all the filled holes. The union of $X_k$ and A contains all the holes and their boundaries. Figure 4(b) is the effect of filling small black holes in Figure 4(a).

3. Results

Segmentation is to subdivide an image into its constituent subregions or objects. The degree of segmentation depends on the problem we are trying to solve. This means that when an object or area of interest has been detected, the segmentation is stopped. For example, in the automatic detection of cell image, we focus on the segmentation of different cells. It makes no sense to go beyond the details required for these elements.

Most segmentation algorithms are based on one of the two basic properties of gray value: discontinuity and similarity. In the first category, gray mutation is mainly considered as the basis of image segmentation, such as edge detection. In the second category, the main consideration is to divide the image into similar regions according to a set of predefined criteria. For example, threshold
processing, regional growth, regional division, and regional aggregation[3]. In practice, it may be a good choice to combine all kinds of methods.

As in the image of adhesion cells overlap is serious, the traditional watershed segmentation algorithm using the area of the cell number and corresponds to the number of local minima in the original image, the noise in the image, irregular shape be mistaken for a local minimum value, thus produced a large number of false edge, outline, caused by excessive division. In order to solve this problem, this study on the target image using marker watershed algorithm in target area for image segmentation [6 -8].

3.1. Watershed Division

Watershed algorithm is a kind of embodiment of edge detection, threshold processing and regional growth, which usually produces more stable results, including the segmentation boundary of the connection. A watershed is based on the three-dimensional rendering of an image. In this "topographic" interpretation, three types of points are considered [3]:

1. Points belonging to the minimum value of a region;
2. Consider a point as a drop of water. If these points are placed in any position, the drop will fall to a single minimum point;
3. The water at this point will flow to more than one such minimum point equally likely.

For a specific regional minimum, the set satisfying the condition (2) is called the catchment basin or watershed of the minimum. The point satisfying the condition (3) forms the peak line of the surface, which is called the dividing line or water dividing line.

The main goal of the segmentation algorithm based on these concepts is to find the water dividing line. The basic idea is very simple: suppose a hole is made in the minimum value of each region, and let the water rise through the hole at a uniform speed, and submerge the whole terrain from low to high. When rising water accumulates in different catchment basins, a dam is built to prevent it. The water will reach a height on the waterline at which only the top of each dam can be seen. The boundaries of these dams correspond to the dividing lines of the watershed. These dividing lines are the boundaries of the connections extracted by the watershed algorithm.

3.2. Watershed Algorithm

M1,M2,……MR represents the coordinate set of the minimum points in the region of image g(x, y). C(Mi) represents the set of points in catchment basin associated with the regional minimum Mi. The symbols Min and Max represent the minimum and maximum values of g(x, y). Let T[n] represent the set of coordinates (s, t) that satisfy g(s, t)<n. That is[3]:

\[ T[n] = \{(s, T) | g(s, T) < n\} \]  

(6)

Geometrically, T[n] is the set of coordinates of points below the plane g(x, y)= n in g(x, y).

As the water level rises from integer n = min+1 to n = max +1, the terrain will be flooded. At any step n of the submergence process, the algorithm needs to know the number of points below the submergence depth. Conceptually, suppose the coordinates in T[n] below the plane g(x, y)= n are "marked" black, and all other marks are marked white. Then, when you look down on the x-y plane at any submerged increment n, you will see a binary image, the black dots of which correspond to the points under the function plane g(x, y)= n.

Let Cn(Mi) represent the coordinate set of points associated with the minimum value Mi of n in the catchment basin at the submergence stage, then Cn(Mi) can be seen as a binary image given by the following formula:

\[ C_n(M_i) = C(M_i) \cap T[n] \]  

(7)

In other words, if (x, y)∈C(Mi) and (x, y)∈T[n] "AND ", is at position (x, y) with Cn(Mi) =1, otherwise the Cn(Mi) =0. The geometric interpretation of this result is that n only needs to use the "AND" operator to separate the binary image in T[n] in the flooded stage.

Next, let C[n] represent the "UNION" of catchment basin that has been submerged by water in stage n:
\[ C[n] = \bigcup_{i=1}^{n} C_n(M_i) \]  
Then, let \( C[\text{max}+1] \) represent the "UNION" of all catchment basins:

\[ C[\text{max} + 1] = \bigcup_{i=1}^{n} C(M_i) \]  

During the execution of the algorithm, the elements in \( C_n(M_i) \) and \( T[n] \) will not be replaced, and the number of elements in the two sets will not increase when increasing, that is, the number of elements will remain the same. In this case, it can be understood that \( C[n-1] \) is a subset of \( C[n] \). Since \( C[n] \) is a subset of \( T[n] \), \( C[n-1] \) can be understood as a subset of \( T[n] \). From this, an important result can be obtained: each connected component of \( C[n-1] \) happens to be included in a connected component of \( T[n] \).

The algorithm for finding the dividing line uses \( C[\text{min}+1] = T[\text{min}+1] \) to initialize. Then the algorithm is used for recursive processing, and \( C[n-1] \) is used to calculate \( C[n] \). The process of computing \( C[n] \) from \( C[n-1] \) is as follows: let \( Q \) represent the set of connected components in \( C[n] \). Then, for each connected component \( q \in Q[n] \), there are three possibilities as follows:[3]:

1. \( q \cap Q[n-1] \) is the empty set.
2. \( q \cap C[n-1] \) contains a connected component of \( C[n-1] \).
3. \( q \cap C[n-1] \) contains more than one connected component of \( C[n-1] \).

Building \( C[n] \) from \( C[n-1] \) depends on which of these three conditions is true. When a new minimum value is encountered, condition 1 occurs. In this case, the connected component \( q \) is UNION into \( C[n-1] \) to form \( C[n] \). When \( q \) is located in some local minimum catchment basin, condition 2 occurs. In this case, \( q \) is UNIONed into \( C[n-1] \) to form \( C[n] \). Condition 3 holds when all or part of the ridgelines separating two or more catchment basins are encountered. Further inundation will result in the convergence of water levels in these catchment basins. Therefore, a dam must be built inside \( q \) to prevent the overflow of the catchment basin.

**4. Discussion**

In the cell image, all the polygons with obtuse angles represent normal cells, while polygons with acute angles represent damaged cells. And the way that you can tell if an image of a cell is obtuse or acute is actually by polygon fitting, which uses polygons to approximate the edges. Let's use an example to discuss the mechanism of this process. Figure 6(a) is a set of non-closed curves. Where A and B are endpoints. By definition, these two points are two vertices of a polygon. At the beginning, take the line AB as the reference, calculate the vertical distance between all other points on the curve and the line AB, and find the vertex with the maximum distance. If the distance exceeds the defined threshold value \( T \), mark it as \( C \), as shown in point \( C \) in Figure 6(a). At this point, the point is declared a vertex of the polygon. Then set up the lines A to C and B to C, so as to get the distance from all points A to C to line AC. Similarly, if this value exceeds the threshold value \( T \), the corresponding maximum distance point is also declared as a vertex E of the polygon. Otherwise, there are no new vertices to declare for the segment. A similar process applies to points between B and C.As shown in Figure 6(b), D is the maximum distance from the line BC, which is also declared as a vertex of the polygon. Figure
6(c) is the result of the next step. Continue this iterative process until the test does not meet the threshold. Figure 6(d) is the final result. The above process is described by algorithm as follows:

1. Let p be a sorted sequence. Obviously, this is a set of boundary points in a binary image. Specify two starting points A and B. They are the two starting vertices of a polygon.
2. Specify a threshold value T, and two empty stacks, "OPEN" and "CLOSED".
3. If the point in p corresponds to a closed curve, put A in the "OPEN" and B in the "CLOSED". If the point in p corresponds to an open curve, put A in the "OPEN" and B in the "CLOSED".
4. Calculate the linear parameters from the last vertex in "CLOSED" to the last vertex in "OPEN".
5. Calculate the distance between the straight line obtained in step 4 and all points in p, and place them in the sequence between the two vertices obtained in step 4. Select the point V_{max} with the maximum distance D_{max}.
6. If D_{max} > T, put V_{max} as a new vertex at the end of the "OPEN" stack. Go to step 4.
7. Otherwise, remove the last vertex from "OPEN" and insert it as the last vertex of "CLOSED".
8. If "OPEN" is not empty, go to step 4.
9. Otherwise, quit. The vertices in "CLOSED" are the vertices of polygons that fit points in p.

Finally, if the polygon above is determined. Then calculate the angle between the two adjacent lines of the polygon, whether it is obtuse or acute, so that you can determine whether the cell is normal or damaged cells, this is much easier. Because this is just a simple use of junior high school mathematics to calculate the angle between the two lines, this paper will not be redundant.

It is determined that there are normal cells (polygon has no acute angle) and damaged cells (polygon has at least one acute angle) between each closed boundary. Then, the area of this region can
be calculated by OpenCV, and the proportion of damaged cells in the whole image can be calculated to complete the analysis and processing of cell image.

5. Conclusion
In this paper, the result after the minimum distance transform image is normalized and the gradient image dot product of ROI are used to suppress useless gradient information, and the labeled watershed algorithm is used to segment cells in the region of interest. The experimental results show that this algorithm can effectively segment adhesion or overlapping cells, and to a certain extent, the boundary of cells can be well segmented. The proposed algorithm established a more accurate dividing line than the traditional marker watershed method, and provided a basis for cell counting and pattern recognition. In addition, this paper creatively applied the polygon fitting method to distinguishing normal cells from damaged cells, and accurately obtained the proportion of damaged cells, which has significant application value.

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