Survey Paper on Object Counting and Detection
Counting Mathematical objects form images

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Abstract— counting the number of similar objects is an integral part of image processing. Knowing the number of similar objects present in the image can be useful for further analysis in a wide range of applications like blood cell counting, fish counting etc. This project implements a simple method for automatically determining the number of similar objects in an image. Once the number of objects are determined the objects per unit area or the density can also be estimated. Existing methods involve counting based on area of objects, color of objects, applying edge detection techniques etc. Manual method must be replaced by computer vision as the results of this method are erroneous and time consuming. Object counting is a challenging problem in image processing. It is routinely carried out in different areas of industries, research institutes, laboratories, agriculture industries among others. Object counting is important for quantitative analysis that depends on estimation of certain elements.

Keywords— object counting, Hough transform, canny edge detection, Segmentation, Feature Extraction

I. INTRODUCTION

A growing number of routine and research activities, in a wide variety of fields, have the counting of certain types of objects (cells, parasitic colonies, etc.) as one of their main components. In most cases, such counting procedure is performed manually, in a process that is often lengthy and tedious. For that reason, several methods for automatically counting the objects of interest have been proposed. The vast majority of those methods rely on digital images containing the objects to provide an estimate as close as possible to the results manually obtained by human experts. The counting problem is the estimation of the number of objects in a still image. It arises in many real-world applications including cell counting in microscopic images, counting of wooden logs from images.

Aim of project is to develop software using which number of similar objects in images can be counted. Figuring out how many similar objects are in an image is required in image analysis. Object counting is used to get certain number of elements from images. These elements act as a source of information for quantitative analysis, motion tracking and qualitative analysis.

Combination of Hough transform and Canny edge detector is used to extract and count features from images. Because automatic counting is objective, reliable and reproducible, comparison of cell number between specimens is considerably more accurate with automatic programs than with manual counting. While a user normally gets a different result in each measurement when counting manually, automatic programs obtain consistently a unique value. Thus, although some cells may be missed, since the same criterion is applied in all the stacks, there is no bias or error. Consistent and objective criteria are used to compare multiple genotypes and samples of unlimited size. Cell counting is very important and useful for medical diagnosis and biological research. Counting microorganisms and colonies is one of
the most basic activities in health tests, food quality control, agriculture analysis etc. Blood count is one of the most commonly performed blood test in medicine. It is required to detect as well as to follow disease treatment. Object counting is also needed in some other research fields where objects cannot be segregated by naked eye and the factors ‘time’ and ‘accuracy’ matter. It becomes challenging when different objects are not easily distinguishable, vary in size and surrounded by noisy background. It is important to notice the variety of objects being counted as the accuracy of development algorithm is dependent on the same [4].

II. REVIEW OF LITERATURE

Object counting is a very common task performed in different industries. Figuring out how many objects in an image is required in image analysis. Object counting is used to get certain number of elements from images. These elements act as a source of information for quantitative analysis, motion tracking and qualitative analysis. The conventional method for object counting is manual, time consuming and in non-automatic form. Continuous counting leads to eye fatigue and affects the accuracy of results. However, the process of counting objects is not always straightforward or trivial, even performed manually. Most counting methods have peculiarities that make them tricky to tackle. For example, the objects may occur in large number and overlapped making counting tricky and tedious that in turn leads to error. Manual method must be replaced by computer vision as the results of this method are erroneous and time consuming.

Because automatic counting is objective, reliable and reproducible, comparison of cell number between specimens is considerably more accurate with automatic programs than with manual counting. While a user normally gets a different result in each measurement when counting manually, automatic programs obtain consistently a unique value. Thus, although some cells may be missed, since the same criterion is applied in all the stacks, there is no bias or error. Consistent and objective criteria are used to compare multiple genotypes and samples of unlimited size. Cell counting is very important and useful for medical diagnosis and biological research. Counting microorganisms and colonies is one of the most basic activities in health tests, food quality control, agriculture analysis etc. Blood cells count is one of the most commonly performed blood test in medicine. It is required to detect as well as to follow disease treatment. Object counting is also needed in some other research fields where objects cannot be segregated by naked eye and the factors ‘time’ and ‘accuracy’ matter. It becomes challenging when different objects are not easily distinguishable, vary in size and surrounded by noisy background. It is important to notice the variety of objects being counted as the accuracy of development algorithm is dependent on the same.

Hough transform in combination with canny edge detection is used to extract features and count objects from images. Pre requirement of Hough transform is that the input image should be edge detected. Different edge detection operations are available, following chart depicts comparison of them.
Table 1. Comparative study of Edge Detectors algorithms

<table>
<thead>
<tr>
<th>Operator</th>
<th>Formulas</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
</table>
| Classical (Sobel, prewitt, Kirsch) | $|G| = \sqrt{G_x^2 + G_y^2}$  
$\theta = \arctan(G_y / G_x)$ | Simplicity, Detection of edges and their orientations | Sensitivity to noise, Inaccurate                |
| Zero Crossing (Laplaci, Second directional derivative) | $|G| = \sqrt{G_x^2 + G_y^2}$  
$\theta = \arctan(G_y / G_x) - 3\pi / 4$ | Detection of Edges and their orientations. Having fixed characteristics in all directions | Responding to Some of the existing edges, Sensitivity to noise |
| Laplacian of Gaussian (LoG) (Marr-Hildreth) | $L(x,y) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$ | Finding the Correct places of edges, Testing wider area around the pixel | Malfunctioning At the corners, curves and where the gray level intensity functions vary. Not finding the orientation of edge because of using the Laplacian filter |
| Gaussian (Canny, Shen-Castan) | $|G| = |G_x| + |G_y|$  
$\Theta = \text{invtan} \ (G_y / G_x)$ | Using Probability for Finding error rate, Localization and response. Improving signal to noise ratio, Better detection specially in Noise conditions. | Complex Computations, False zero crossing, Time consuming, noise tolerant. |

Cranny’s edge detection algorithm has a better performance. The evaluation of the images showed that under the noisy conditions, canny algorithm exhibited better performance.
Counting of objects requires certain features to be extracted from image. Several feature detection methods are available. Chart below gives comparison of different such methods.
<table>
<thead>
<tr>
<th>Sr.no</th>
<th>Name</th>
<th>Distinct features</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
</table>
| 1     | Thresh holding  | The simplest thresholding methods replace in an image with a black pixel if the image intensity is less than some fixed constant T or a white pixel if the image intensity is greater than that constant | 1.simple to implement  
2.faster  
3.good for some kind of images like documents, controlled lightning | No guarantee of object coherency, it may contain gaps or holes |
| 2     | Template matching | Template matching is conceptually simple process. We need to match a template to an image, where the template is a sub image that contains the shape we are trying to find. | It can be used in manufacturing as a part of quality control, a way to navigate a mobile robot, or as a way to detect edges in images. | Less accurate as slight deviations in shape, size, orientation, would prevent template matchers from detecting shapes |
| 3     | Hough Transform | The Hough transform is a feature extraction technique used in image analysis, computer vision, and digital image processing. It is used to detect shapes described by some mathematical equations. | 1.Tolerant to gaps in images  
2.Less affected by noise in images  
3.Tolerent to occlusion in images | Only efficient if a high number of votes fall in the right bin. This means that the bin must not be too small, or else some votes will fall in the neighboring bins, thus reducing the visibility of the main bin. |

The Hough Transform is tolerant of gaps in the edges. It is relatively unaffected by noise. It is also unaffected by occlusion in the image.
III. SYSTEM DESIGN

3.1. System Architecture
Following is software based approach to count a number of objects from images

![Diagram of system architecture](image)

**Figure 3.1. Generalized frameworks for object counting using image processing**[^4]

3.1.1. Image Capture
This step intends to capture image through camera. The quality of image depends on camera Parameters, lighting conditions, size of objects and distance from which image is taken. For better results, cameras with higher resolution are preferred[^4].

3.1.2. Image Pre-processing
Image pre-processing is a technique of adjusting images suitable for the next step of computational process. In this work we use simple image processing technique to enhance the image .We first convert the input image into HSV image. From this HSV image, we precede the analysis of the saturation component S, because the S image shows clearly the bright objects. Descriptions in terms of hue/lightness/Chroma or hue/lightness/saturation are often more relevant For the most part, computer vision algorithms used on color images are straightforward extensions to algorithms designed for grayscale images, for instance k-means or fuzzy clustering of pixel colors, or canny edge detection. At the simplest, each color component is separately passed through the same algorithm. It is important, therefore, that the features of interest can be distinguished in the color dimensions used. Because the R, G, and B components of an object’s color in a digital image are all correlated with the amount of light hitting the object, and therefore with each other, image descriptions in terms of those components make object discrimination difficult. Descriptions in terms of hue/lightness/Chroma or hue/lightness/saturation are often more relevant[^2].

3.1.3. Segmentation
In this stage the concept of the intensity difference between red blood cell and other cells is used to segment RBC from other cells. After applying pre-processing stage, the outcome image is feeding to the segmentation stage. Segmentation is carried out based on histogram thresholding and morphological operations. Mathematical morphology is a major tool for segmenting images and also it is useful to describe region shape such as region shape, skeleton, boundaries and texture. First step in this segmentation stage is to find out lower and upper threshold value from histogram image of saturation image. Then divide the saturation image into two binary images based on these threshold values. Thresholding is one of the techniques used for to segment the objects from background by selecting any point T from the image. Take any point in the image, consider (x, y) for which f(x, y) > T is called an object point, else the point is called background point. The mathematical representation of thresholding operation is expressed as;

[^4]: Figure source: [Image source](image)
[^2]: Description source: [Reference number]
Where pixels labelled 1 are corresponding to the object pixels otherwise it is background pixels. Morphological operation is applied to two binary images with lower and higher pixels values. This allows the straightforward extraction of small light or dark structures regardless of their shape.

\[
g(x, y) = \begin{cases} 
1 & \text{if } f(x, y) > T \\
0 & \text{if } f(x, y) \leq T 
\end{cases}
\]  

(1)

3.1.4. Edge Detection

Edge detection includes a variety of mathematical methods that aim at identifying points in a digital image at which the image brightness changes sharply or, more formally, has discontinuities. The points at which image brightness changes sharply are typically organized into a set of curved line segments termed edges \[^2\].

3.1.4.1. Canny edge detection

Step 1: Gaussian filtering to remove noise

The first step of canny edge detection is to filter out any noise in the original image before trying to locate and detect any edges. The Gaussian filter is used to blur and remove unwanted detail and noise. By calculating a suitable 5 X 5 mask, the Gaussian smoothing can be performed using standard convolution method.

Step 2: Sobel Operator

After smoothing the image and eliminating the noise, the next step is to find the edge strength by taking the gradient of the image. The Sobel operator performs a 2-D spatial gradient measurement on an image. The gradient magnitude is given by: Then, the approximate absolute gradient magnitude (edge strength) at each point can be found by the formula below which is simpler to calculate compared to the above exact gradient magnitude. Approximate gradient magnitude given below: \[|G| = |G_x| + |G_y|\]. The Sobel operator uses a pair of 3x3 convolution masks, one estimating the gradient in the x-direction (columns) and the other estimating the gradient in the y-direction (rows). Sobel Gx and Gy masks shown below each one estimates gradient x direction and y direction respectively:
Step 3:
Finding Gradient angle Finding the edge direction is trivial once the gradient in the x and y directions are known. However, you will generate an error whenever sum of Gx is equal to zero i.e. Gx value in denominator meaning calculating arc tan of infinity. So the edge direction will equal to 90 or 0 degrees depend on Gx value and 0 degrees depend on Gy value. The formula for finding the edge direction is given below: \( \theta = \tan^{-1} \left( \frac{G_y}{G_x} \right) \).

Step 4:
Tracing the edge in the image using \( \theta \) (angle) once the edge direction is known, the next step is to relate the edge direction to a direction that can be traced in an image. So if use the 5x5 matrix to calculate the angle of the edge, the smaller the matrix the fewer angles would have in the image.

Step 5: Non maximum Suppression
After the edge directions are known, non-maximum suppression is applied. No maximum suppression is used to trace along the gradient in the edge direction and compare the value perpendicular to the gradient. Two perpendicular pixel values are compared with the value in the edge direction. If their value is lower than the pixel on the edge then they are suppressed i.e. their pixel value is changed to 0, else the higher pixel value is set as the edge and the other two suppressed with a pixel value of 0.

Step 6: Hysteresis
Finally, hysteresis is used as a means of eliminating streaking. Streaking is the breaking up of an edge contour caused by the operator output fluctuating above and below the threshold. If a single threshold, \( T_1 \) is applied to an image, and an edge has an average strength equal to \( T_1 \), then due to noise, there will be instances where the edge dips below the threshold. Equally it will also extend above the threshold making an edge look like a dashed line. To avoid this, hysteresis uses 2 thresholds, a high and a low. Any pixel in the image that has a value greater than \( T_1 \) is presumed to be an edge pixel, and is marked as such immediately. Then, any pixels that are connected to Image processing 11 this edge pixel and that have a value greater than \( T_2 \) are also selected as edge pixels. If you think of following an edge, you need a gradient of \( T_2 \) to start but you don't stop till you hit a gradient below \( T_1 \).
3.1.5. Feature Extraction Using Hough Transform
The morphological operations, logical operations and Hough transform technique are used in this stage to extract the red blood cells from other cells and background. Morphological and XOR operation are applied on two binary images. After that Hough transform is applied to this image to extract object [4].

3.1.5.1. Circular Hough Transform
The Idea of the Hough transformation is to convert image space into a parameter space. This conversion is a mapping that analyses the image looking for a special sort of parameterized features usually lines or circles. Its beauty lies in the many different shapes that can be detected together with their parameters. In this seminar we are going to deal only with the special case of lines. Assuming the reader is familiar with the parametric representation d = \cos(\Theta) \cdot x + \sin(\Theta) \cdot y of a line, where \Theta is the angle between the line and the x-axis, d the distance to the origin and any (x, y)^T which verifies the equation a point on that line, the Hough transformation for lines is a relatively simple construct. The concept is to create a number of bins for lines of a certain range of their parameters (d, \Theta) to (d_0, \Theta). A bin is an accumulator cell for that range of parameters. For each edge point in image space we can assign a bin by taking the pixel position and gradient direction into account. We can employ Sobel to extract both gradient magnitude and angle, or alternatively any other means to do the same thing. Pixels along a straight edge all contribute to the same bin, because lines through these pixels of their gradient direction all have about the same distance to the origin. The fullest bins represent the most prominent or “best” lines. For a better fit the parameters used for that line can for instance be computed as the mean parameters of all edge pixels that contributed to that bin. Be aware that the number of bins used influence the minimum “difference” of two lines that are to be differed. Using too many bins “blurs” the maxima. Noise influences gradient information and pixels from the same original linear edge may fall into two neighboring bins when the bins are too small [4].

Circular Hough Transform will be applied on the image. The Hough Transform (HT) has been recognized as a very powerful tool for the detection of parametric curves in images. It implements a voting process that maps image edge points into manifolds in an appropriately defined parameter space. The Circular Hough Transform (CHT) is one of the modified versions of the HT. The CHT concentrates to find circular patterns within an image. The Circle Hough Transform is designed to find a circle characterized by a center point (x_0, y_0) and a radius r. A circle pattern is described by equation 2.

\[(x - X_0)^2 + (y - y_0)^2 = r^2\] (2)

Where x_0 and y_0 are the coordinates of the center and r is the radius of the circle. The conventional CHT is working based on the voting procedure. Table 1 presents the radius parameter for each 5 set of images collected from different sources.

<table>
<thead>
<tr>
<th>Image</th>
<th>Radius</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Minimum</td>
</tr>
<tr>
<td>1</td>
<td>32</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>8</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

Template for red blood cell is created using parameter values such as radius and center then voting procedure is done using this template matching [2].
The input image for CHT is edge detection image using any edge detection algorithm such as canny edge detection algorithm \(^2\).

### 3.1.5.2. Linear Hough Transform

Lines can be represented uniquely by two parameters. Often the form in Equation 3 is used with parameters \(a\) and \(b\).

\[
y = a \cdot x + b \tag{3}
\]

This form is, however, not able to represent vertical lines. Therefore, the Hough transform uses the form in Equation 4, which can be rewritten to Equation 5 to be similar to Equation 3. The parameters \(\theta\) and \(r\) is the angle of the line and the distance from the line to the origin respectively.

\[
\begin{align*}
r & = x \cdot \cos \theta + y \cdot \sin \theta \leftrightarrow \\
\cos \theta & = \frac{r}{\sin \theta} \\
y & = -\frac{\sin \theta}{\cos \theta} \cdot x + \frac{r}{\sin \theta} \tag{5}
\end{align*}
\]

The Hough space for lines has therefore these two dimensions; \(\theta\) and \(r\), and a line is represented by a single point, corresponding to a unique set of parameters \((\theta_0, r_0)\). The line to-point mapping is illustrated in Figure 3.3\(^8\).

### 3.1.6 Object Counting

As a result obtained from the in Figure 3.2, the red blood cells showed in black color and background
in white. By using filter, the noise are removed from this image, then it act as the input image for Circular Hough transform technique. This technique is the final step of counting red Blood cells in the image. For this process the center point of red blood cells are needed. In order to estimate the center point of each circle the radius of circle is needed. So we have to find out the minimum and maximum radius of circles in the image using the command available in Matlab imdistline. Then the CHT is applied when both radiuses are known. The accumulator space is created using CHT. It is given in equation

\[
\begin{align*}
X_0 &= r \sin \theta \\
y_0 &= r \cos \theta \\
\text{where } r \in (\text{minr, maxr})
\end{align*}
\] (6)

Red blood cell detection is done through this accumulator space. It is shown in Figure 3.4. Red blood cell detection indicated by circle surrounded by blue color. From this we can count the number of red blood cells using circular Hough transform technique.

![Figure 3.4 Accumulator space & detection](image)

**IV. CONCLUSION**

Image processing techniques are helpful for object counting and reduce the time of counting effectively. Hough transform is used to detect shapes from image. It can prove useful in medical industry to count number of blood cells. Field where accuracy and time to count matters, this approach plays vital role because manual method of counting is not reliable. The object counting methods must be automated to achieve accuracy and speediness. Object counting is also needed in some other research fields where objects cannot be segregated by naked eye and the factors ‘time’ and ‘accuracy’ matter.

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