COURSE : DIGITAL IMAGE PROCESSING

COURSE CODE: SWE1010

SLOT: A2+TA2

FACULTY: ASNATH VICTY PHAMILA Y

PROJECT TITLE:

AUTAOMATION OF COUNTING OBJECTS IN A IMAGE USING IMAGE PROCESSING TECHNIQUES

TEAM MEMBERS:

P.NITYASREE-17MIS1007

ABSTRACT:

This project discuss about techniques of object detection that are used to count the number of objects on the image. Our aim is to estimate accurate count of object in the image. So we are going to develop a program which detects the objects in an image.

The program should automatically detect the desire object and count the number of objects in that image by detecting the edges of an image. We are going to estimate density of image whose integral over any image region gives us count of objects within that region.

KEYWORDS:

Counting objects, Edge detection, Binary image, Canny Edge Detection

INTRODUCTION:

Object counting is a very common task performed in different industries.

Finding 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.

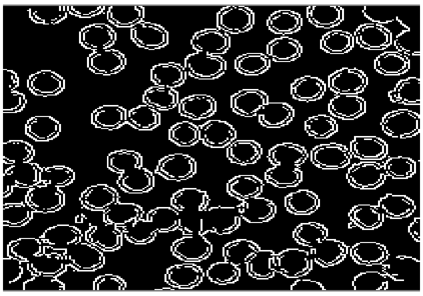
Because automatic counting is objective, reliable and reproducible, comparison of cell number between specimens is considerably more accurate with automatic programs than with manual counting. While a user normally gets a different result in each measurement when counting manually, automatic programs obtain consistently a unique value.

The program should automatically detect and count the total number of object from image. In the process of object detection, targeted object which is uncertain due to presence of other object is one of the main problem faces in image processing field.

PROCESS:

Canny Edge Detection:

The high pass filtered image is passed through the canny edge detection algorithm which detects the edges of the cells. It includes many sub functions involving double thresholding, differentiation of the image based on the change in the intensity and avoiding the false edges. The secondary edges in the image are obtained by using connected components methodology removing and edge detection are performed at this stage.



Closing Morphological Operation: Closing is Dilation followed by Erosion. It is useful in closing small holes inside the foreground objects and the small points on the image. This is useful for connecting the small gaps present in the edges of the cells.

Contouring The image*:* Contours are closed regions in the image which are obtained by the canny edge detection algorithm. These contours are found in the image, which indirectly represent the cells present in the image. The basic idea of the red blood cells counting was to use three major techniques which are logical, morphology and contour detection

LITERATURE REVIEW:

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 .

In marine science research, fish population estimation and fish species classification is important for the assessment of fish abundance, distribution and diversity in marine environments .

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**.**

FRAMEWORK

The general method for object counting follows the following framework:

1. Image Acquisition:

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.

2. Image Enhancement:

Objective of image enhancement is to process image so that resulting image is more suitable than original image for specific application. During this process, one or more attributes of image are modified. The choice of attributes and the way in which image should be modified depend on specific application. These include basic gray level transformations, histogram modification, average and median filtering etc.

3. Image Segmentation:

Segmentation is used to partition an image into distinct regions containing each pixel with similar attributes. The result of segmentation is set of segments that collectively cover entire image or set of contours extracted from image. It can be region based segmentation or data clustering or edge based segmentation.

4. Object Counting:

Object counting is done get number of segmented areas. Some of the methods of object counting are blob analysis, connected components analysis, statistical area measurements etc.

IV. APPLICATIONS

Object counting using image processing has huge applications where automation is to be introduced and time of counting is to be reduced.

Some of the main applications of object counting in industrial systems are packaging, quality control, and so on.

It is helpful in the research areas where objects are of very small size. Object counting algorithm can be also used to track and identify objects.

The present methods can be extended to have counting system based on userselected attributes.

V. CONCLUSION

Image processing techniques are helpful for object counting and reduce the time of counting effectively. Proper recognition of the object is important for object counting.

The accuracy of the algorithm depends on camera used, size of objects, whether or not objects touching and illumination conditions.

SAMPLE CODE:

```
from matplotlib import pyplot as plt

from skimage import data

from skimage.feature import blob_dog, blob_log, blob_doh

from math import sqrt

from skimage.color import rgb2gray

import glob

from skimage.io import imread


example_file = glob.glob(r"microbes.jpg")[0]

plt.show(example_file)

cm_gray = plt.get_cmap()

im = imread(example_file, as_grey=True)

plt.imshow(im, cmap=cm_gray)

print("InputImage")
```

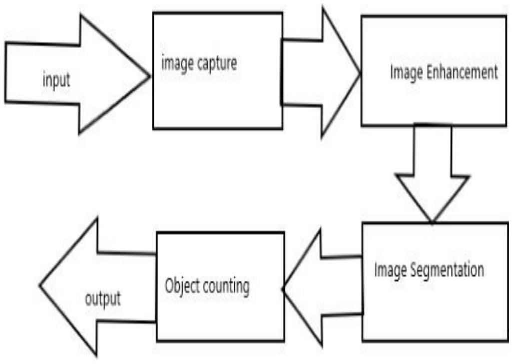
```
plt.show()


blobs_log = blob_log(im, max_sigma=30, num_sigma=10, threshold=.1)


blobs_log[:, 2] = blobs_log[:, 2] * sqrt(2)
numrows = len(blobs_log) print("number
of objects: " ,numrows)


print("OutputImage") fig,
ax = plt.subplots(1, 1)
plt.imshow(im, cmap=cm_gray)
for blob in blobs_log:
   y, x, r = blob
   c = plt.Circle((x, y), r+5, color='lime', linewidth=2, fill=False)
   ax.add_patch(c)
plt.show()
```

ARCHITECTURE AND SYSTEM MODEL:



There are number of approaches for counting objects problems in an unsupervised way, where as in supervised learning we can categorize into two:

1. Counting by using object detection.
2. Counting by using object regression.

Counting by using object detection:

In this method visual object detector is used, that localizes individual object instances in the image. If localizations of all instances given, counting becomes trivial. However, object detection is very far from being solved, especially for overlapping instances.

In particular, most current object detectors operate in two stages:

1. Producing a real-valued confidence map; and
2. Given such a map, a further thresholding and non-maximum suppression steps are needed to locate peaks corresponding to individual instances.

Alternatively, several methods assume that objects tend to be uniform and disconnected from each other by the distinct background colour, so that it is possible to localize individual instances via a Monte-Carlo process, morphological analysis or variational optimization.

Counting by using object regression:

These methods avoid solving the hard detection problem. Instead, a direct mapping from some global image characteristics (mainly histograms of various features) to the number of objects is learned. Such a standard regression problem can be addressed by a multitude of machine learning tools (e.g. neural networks.

This approach however has to discard any available information about the location of the objects (dots), using only its 1-dimensional statistics (total number) for learning. As a result, a large number of training images with the supplied counts needs to be provided during training. Finally, counting by segmentation methods can be regarded as hybrids of counting-by-detection and counting-by-regression approaches.

They segment the objects into separate clusters and then regress from the global properties of each cluster to the overall number of objects in it.

This project shows some of the applications of our project like counting stars in the open sky image, detecting objects on the image in industrial process control systems, for counting silica particles in the glass at microscopic level in glass industry, monitoring crowds in surveillance systems and performing wildlife census or counting the number of trees in aerial image of a forest.

Detection of Bacterial cells in fluorescence-light microscopy images:

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. In marine science research, fish population estimation and fish species classification is important for the assessment of fish abundance, distribution and diversity in marine environments. 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.

The methods used are:

1. The proposed density-based approach.
2. The counting-by-regression baseline.
3. The counting-by-detection baseline.
4. Application-specific method.

1. The proposed density-based approach:

In this method a very simple feature representation was chosen, in this some entries are constructed by means of SIFT descriptors extracted from the hold-out any number of images.

2. The counting-by-regression baseline:

Each of the training images was described by a global histogram of the entries occurrences for the same codebook as above. Here we can learn two types of regression (ridge regression with linear and Gaussian kernels) to the number of cells in the image.

3. The counting-by-detection baseline:

In this method detector is trained based on the linear SVM classifier and for sample positive examples SIFT descriptors corresponding to the dotted pixels whereas for negative examples Delaunay triangulation is built on the dots and took SIFT descriptors corresponding to the Delaunay edges. At the time of detection SVM is applied at each pixel.

4. Application-specific method.

In this software is used which is specifically designed for analysing cells in fluorescence-light images. The counting algorithm here is based on adaptive thresh-holding and morphological analysis. The objective minimized during the validation was counting accuracy.

EXPLAINATION OF ALL THE MODULES:

Some more methods used for counting microorganism colonies in an image:

This invention relates to a method and apparatus for counting the number of distinct objects in a scanned image. In particular, it relates to a method and apparatus for counting the number of microorganism colonies present on a substantially planar substrate.

Different methods and devices are known for counting microorganism colonies for

example, ***petri dishes***.

The primary disadvantage is the expensive and sophisticated equipment used in such systems to process the raw pixel image produced by the video cameras. To avoid multiple counting of the same colonies such systems typically include processing-intensive labelling schemes requiring relatively powerful computer systems to accurately count of the number of colonies in an acceptable amount of time.

An additional disadvantage is that many of these video-based systems require that the petri dishes be illuminated through their bottom surface which requires a substrate which is light permeable to ensure accurate counting

In addition to the cost and complexity of the hardware configurations of known automated video counting systems, the object counting algorithms used with systems employing digitization of the images also suffer from disadvantages. A simple Euler number can be used to identify objects in a raster-scanned image and can be used with only a single pass through the image, but detects only 4-connected objects. This can give spurious results when 8-connected images are present in the scanned image. At the opposite extreme, a full-connected component analysis detects all objects, whether they are 4-connected or 8-connected. That type of analysis, however, involves complicated-labelling and tagging operations which can require multiple passes through the image, as well as significantly more complex and costly hardware.

1. A method of counting microbial colonies growing in a solid medium on a substantially planar substrate culture device comprising the steps of

a) Incrementally scanning substantially straight lines across the planar substrate culture device to generate a first line pixel data and a second line pixel data corresponding to detected colonies;

b) Storing the first line pixel data and at least two pixels from the second line pixel data;

c) Changing the position of the planar substrate culture device to scan incremental lines of the planar substrate, wherein the number of colonies growing in the solid media is a total of the recorded object starts minus recorded object merges.

2. A microbial colony counting apparatus comprising

1. A linear array of light sensitive detectors intersecting a substantially planar substrate culture device containing microbial colonies growing in a solid medium.

2. The processing means to record and manipulate the pixel values measured by the detectors. Indexing means for incrementally changing the position of the planar substrate relative to the detectors to provide more than one indexed position of the planar substrate wherein the change of position is substantially perpendicular to the, substantially straight line intersection of the linear array with the planar substrate.

3. The linear array of light sensitive detectors comprise a CCD sensor array.

4. Further comprising a light source positioned to produce light striking an upper surface of the substantially planar substrate and which is capable of providing light having a substantially uniform intensity across the substantially straight line inner section at the linear array with the planar substrate.

5. The light source is a linear LED array.

6. Further comprising focusing means for focusing light reflected from an upper surface of the substantially planar substrate to the detectors.

7. The focusing means comprise a linear array of lenses.

8. The linear array of lenses comprise a linear array of SELFOC lenses.

9. The indexing means comprise an incremental stepper motor operatively connected to at least one roller for changing the position of the planar substrate.

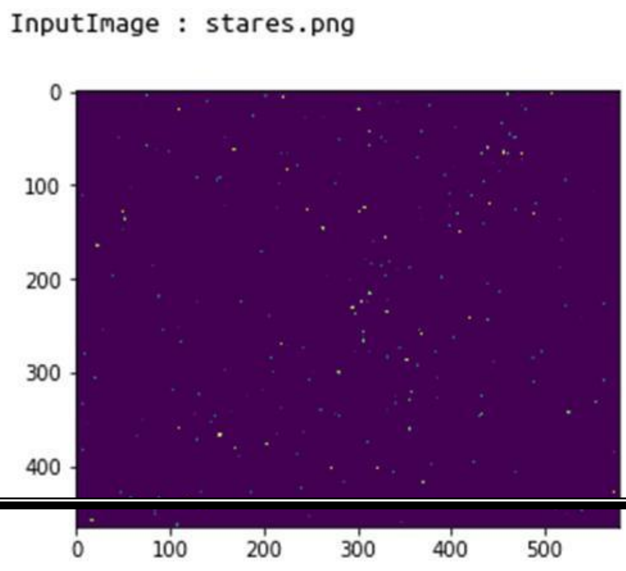
Counting the objects on the image by boundary detection

Edges are not the same as occluding contours, because many effect changes in albedo, shadow boundaries, fast changes in surface normal can create edges. Rather than relying on the output of an edge detector, we could explicitly build an occluding contour detector, using the sliding window recipe. At each window, we would look at a set of relevant features within the window, then use these to decide whether the pixel at the centre of the window is an occluding contour or not. In practice, it is sometimes more useful to produce the posterior probability that each pixel lies on a boundary, at that pixel.

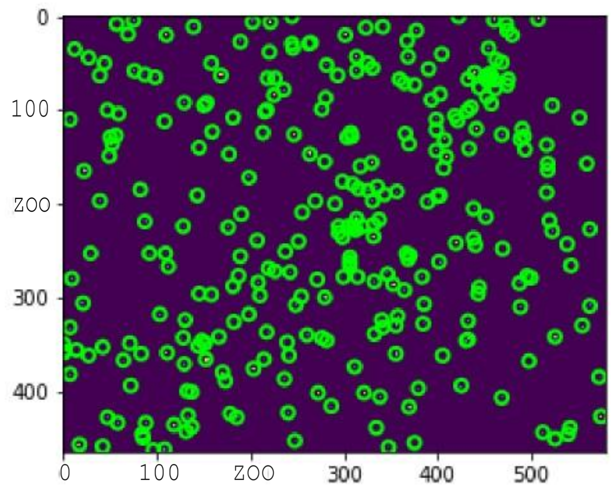
Probability of boundary is now widely used as a feature, and implementations are available. The most recent variant is global probability of boundary, which gets improved results by linking the probability of boundary method to a segmenter, and so filling in pixels that are required to

RESULT AND DISCUSSION:

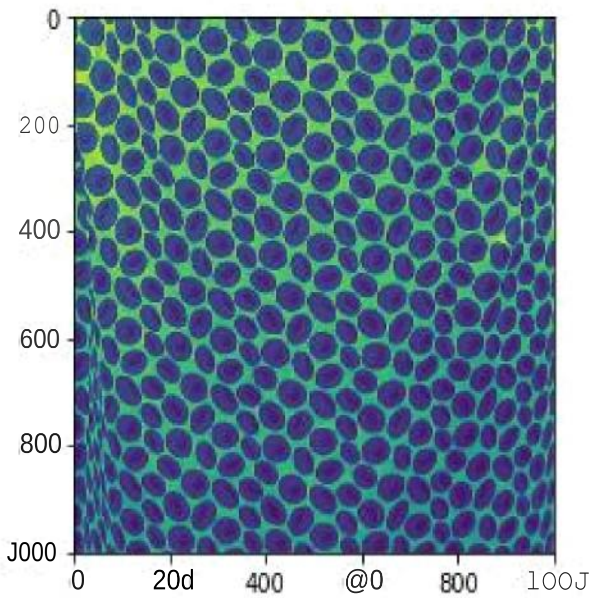
OUTPUT:

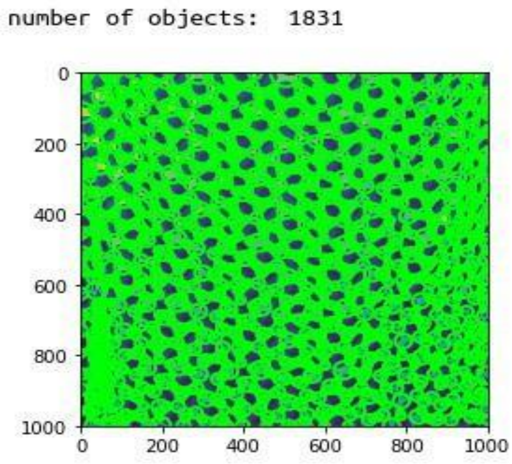


nunber of objects : 298



InputIma9e : RBC.jpg





Summary :

• The separation of detection quality and detection quantity. New performance graphs allow us to easily perceive the detection quantity (“how many objects have been detected?” and “how many false alarms have been detected?”) as well as detection quality (“how accurate is the detection of the objects?”).

• The influence of the data base is evaluated, i.e., the relationship between the performance of the detection algorithms and the structure of the image test database is put forward. This makes it easier to grasp the advantage an object detection algorithm might have when it is tested on an image collection which larger percentage of relevant information.

• The derivation of a single performance value which does not depend on quality related thresholds. Although this performance value, by definition, does not allow us to fully comprehend the behaviour of a detection algorithm, it makes it easier to create a ranking of the algorithms to evaluate.

CONCLUSION:

Our aim is to estimate accurate count of object in the image. So we are going to develop a program which detects the objects in an image.

The program should automatically detect the desire object and count the number of objects in that image by detecting the edges of an image. We are going to estimate density of image whose integral over any image region gives us count of objects within that region.

REFERENCES

1. Lempitsky, V., & Zisserman, A. (2010). Learning to count objects in images. In *Advances in Neural Information Processing Systems* (pp. 1324-1332).

2. Rabaud, V., & Belongie, S. (2006, June). Counting crowded moving objects. In *Computer Vision and Pattern Recognition, 2006 IEEE Computer Society Conference on* (Vol. 1, pp. 705-711). IEEE.

3. Floeder, S. P., Graessle, J. A., Schultz, J. C., Schwarz, W. R., & Waltz, F. M. (1995). U.S. Patent No. 5,403,722. Washington, DC: U.S. Patent and Trademark Office.

END