AUTOMATION OF COUNTING OBJECTS IN AN IMAGE USING IMAGE PROCESSING TECHNIQUES

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***Abstract*— This paper discuss about methods or 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. Figuring out how to gather such image density can be planned as a minimization of a regularized risk quadratic cost function**.

Keywords—counting objects, edge detection, binary image.

I. INTRODUCTION (*HISTORY)*

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. Automatic counting of objects is a subject that has received significant attention in last few years with objects as varied as cells, RBCs, fish, eggs.

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.

Identifying and finding item and discovering number of articles in digital image has turned out to be one of the significant applications for modern use to ease user and spare time. This strategies has been develop years prior yet change of it is still require with a specific end goal to accomplish the focused on objective in more efficient and accurately. The trouble of these tasks increments impressively with obstacles and along these lines with more crowds. At the point when the items constrained to be of a similar kind, notwithstanding, partitioning of densely crowded semi-inflexible objects can be accomplished by methods for bunching tracked feature points. The goal of this project is to detect and allocate the object using few method such as colour processing and shape detection, edge detection of the image. 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. This is due to the object are not clearly expressing in the image and will assume and eliminated by the program. Besides that, objects which overlapping each other also made the process challenging where hidden object will be detected and counted and the total number will be no accurate.

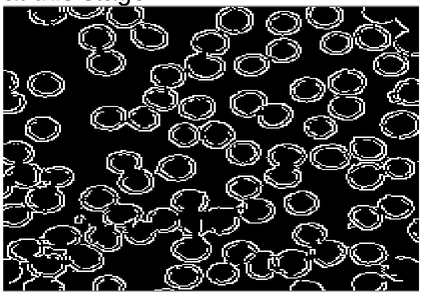
The counting problem is estimating of number of objects present in an image or video frame. It can be used in many real world applications like counting stars in the open sky image, detecting objects on the image in industrial process control systems, for counting silica particles in the glass at microscopic 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.

Dotting (pointing) is the regular way to count objects for people, in any event when the number of objects is more. This paper builds up a straightforward and general discriminative learning-based structure for including objects in the image. Be that as it may, not at all like such techniques, the approach additionally takes full and broad utilization of the spatial information contained in the dotted supervision.

This work addresses the problem of segmenting moving objects in video or gifs of dense crowds. While our rousing issue is that of counting humans in crowd footage, our approach likewise has applications to more general groups of objects such as herds of animals or migrating cells. We only require that the crowd be homogeneous, i.e., composed of different instances of the same object class.

II. 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 subfunctions 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.



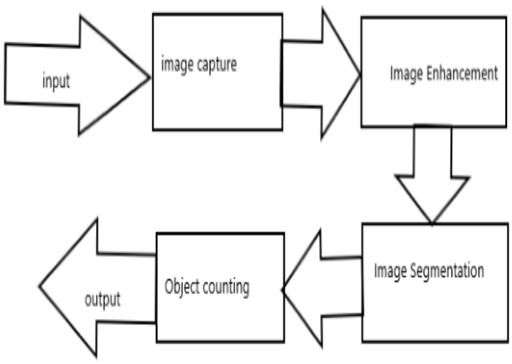
Canny edge detection

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 arelogical, morphology and contour detection

III. SURVEY ON PAPERS

Architecture:



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: first producing a real-valued confidence map; and second, given such a map, a further thresholding and non-maximum suppression steps are needed to locate peaks corresponding to individual instances. More generative approaches avoid non-maximum suppression by reasoning about relations between object parts and instances, but they are still geared towards a situation with a small number of objects in images and require time-consuming inference. 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.

Methods in these groups deliver accurate counts when their underlying assumptions are met but are not applicable in more challenging situations.

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.

Now we will discuss 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.

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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.

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 in, for example, ***petri dishes***. Manual counting of colonies by trained laboratory personnel is well-known. This method has many disadvantages. They include the costs associated with the use of skilled technicians to perform the time consuming chore of manual counting as well as the limited accuracy in the counts achieved. Video-based systems suffer from a number of disadvantages. 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. The illumination is typically required because of the thickness of the agar used in petri dishes results in colonies growing on the surface of the agar as well as in the middle and on the bottom of the agar. Surface illumination only would result in under counting of the colonies in the middle and on the bottom of the agar. The growth of colonies throughout the vertical thickness of the medium is not a particular problem for lasers of the disposable microorganism culturing devices such as PETRIFILM TM, manufactured by 3M Company. Such devices have a very thin layer of growth medium making all colonies visible with surface illumination. The substrate is not, however, sufficiently permeable to light for use with many of the known automated counting systems. 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.

The ***second category*** of automated counting systems typically uses an array of photo detectors and hard wired circuitry to perform the counting process. As with most of the video-based systems, the counting systems using photo-detectors are also limited by the requirement that the petri dish be illuminated through its substrate to produce an accurate count. As a result, the substrate on which the colonies are contained must be light permeable, which is a particular problem with disposable culturing devices such as PETRIFILM TM.

Method which eliminates the disadvantages of petri dishes

The present invention eliminates the disadvantages of the known systems as described above. In particular, the present invention does not require illumination through the substrate and is adapted for use with microorganism culturing devices having a substantially planar substrate, such as PETRIFILM TM. The present invention also provides a fast and accurate count of colonies using readily available linear arrays of light sources, lenses and image sensors-many of which were developed for use in facsimile or photocopying machines. These components are connected to readily available microprocessors and use the algorithm described below to accurately and quickly perform the counting process without labelling or long-term storage of the data to avoid multiple counting of individual colonies.

In its simplest form, the preferred apparatus of the present invention includes a LED bar illuminating the surface of the substrate and a linear array of SELFOC lenses which focus the light reflected off of the substrate onto a linear CCD sensor array. The CCD sensor array is connected to a microprocessor which analyses the raster-scanned data using the preferred algorithm.

In the preferred embodiment, the apparatus is electrically connected to a remote computer for automatic data transfer and storage. The preferred image processing system includes an automatic calibration feature which calibrates the sensors by scanning a blank substrate to determine a threshold level above which objects will be counted. Also contemplated for use in the present invention is a cassette mechanism to automatically feed a number of substrates through the scanning apparatus in a manner similar to the automatic feeding of paper through a photocopying machine.

Barcode labels can also be incorporated into the culturing devices to simplify the transfer of information from the preferred apparatus to other electronic equipment. In the preferred apparatus, the LED array and CCD sensors used to detect colonies are also used to read the barcode labels. The preferred algorithm developed for use with the present invention also offers advantages not available with known object counting algorithms. Like Euler number analysis, the preferred algorithm can be used with only a single pass through the image. Its advantage over the Euler number analysis is that the preferred algorithm can detect 8-connected objects in addition to the 4 connected images to which Euler number analysis is limited. The preferred algorithm does so without requiring multiple passes through the image or the complexity and cost associated with a fully connected component analysis algorithm including labelling of the pixels from the entire image. In addition, the preferred algorithm is particularly useful for inspection tasks requiring relatively high image processing speeds because its use of raster scanned data and limited processing neighbourhood is tailored for high-speed data processing using relatively simple hardware. In contrast, the known systems described above require complex hardware configurations to implement complex data analysis schemes. As a result, they typically cost $10,000 or more. These and various other advantages and features which characterize the present invention are pointed out witch particularity in the claims annexed hereto and which form a part hereof. However, for a better understanding of the invention, its advantages, and the objects obtained by its use, reference should be made to the .drawings which form a further part hereof, and to the accompanying descriptive matter, in which there are illustrated and described preferred embodiments of the invention.

The preferred ***algorithm for counting the number of distinct objects*** in the scanned area of the substrate is described below. In essence, the algorithm searches the data stream to detect object starts and object merges. The total number of distinct objects in a scanned image is equal to the number of the object starts minus the number of object merges. It will be understood by those skilled in the art that many other algorithms could be used to scan objects such as substrates having microorganism colonies located on them. Examples of algorithms include the SRI (Stanford Research Institute) algorithm or Euler number analysis. The present invention is, however, most advantageously used with the preferred algorithm described below. The preferred algorithm is designed for use with a raster-scanned data format to provide high speed in section capabilities. That format treats the image as a two-dimensional array of data which may only be accessed along successive rows in a left-to-right manner. As a result, it is difficult to access more than a small portion of the image at any single time. The pixel of interest passes through the image in a raster scanning manner and, thus, the portion of the image available for processing must also pass through the image with the pixel of interest. The preferred algorithm uses the sigma-shaped neighbourhood depicted image processing. The addition of the fifth pixel to the standard processing neighbourhood allows for 8-connected object analysis not available with Euler number analysis.

Also, because any given pixel is either part of an object or part of the background, grey level images are preferably converted to a binary format where the object is white and the background is black. That conversion is accomplished before the data is processed with the preferred algorithm. In use, the algorithm passes the sigma region across the image in a raster-scanned Order so that pixel, the pixel of interest, is centred on each pixel in the image exactly.

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In spite of this failing, the preferred apparatus and algorithm provide colony counts that are well within the allowed margin of error as compared to manual counting. In addition, the preferred method of use includes the manual screening of the substrates prior to automated counting to remove those substrates in which the colonies have merged to form a global colony which would likely be miscounted by the present invention.

That failure exists because, for any given merge condition, the algorithm cannot discern whether the two branches surrounding the hole are distinct or if they had split from a single object farther above in the image. This problem cannot be remedied without a complicated and expensive global object labelling feature which defeats many of the advantages accompanying the preferred algorithm and apparatus. In spite of this drawback, the present algorithm does count the vast majority of objects with sufficient accuracy to be very useful in many image processing tasks.

It is to be understood, however, that even though numerous characteristics and advantages of the present invention have been set forth in the foregoing description, together with details of the structure and function of the invention, the disclosure is illustrative only, and changes may be made in detail, especially in matters of shape, size and arrangement of parts within the principles of the invention to the full extent indicated by the broad general meaning of the terms in which the appended claims are expressed.

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

a) A linear array of light sensitive detectors intersecting a substantially planar substrate culture device containing microbial colonies growing in a solid medium, wherein the detectors intersect the planar substrate in a substantially straight line and measure pixel values in the linear array, wherein pixels values on a white side of predetermined threshold are recorded as a value of O and pixel values on a black side of the threshold are recorded as a value of l.

b) The processing means to record and manipulate the pixel values measured by the detectors.

c) 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.

Detecting Humans in an image and counting humans

Being a pedestrian is dangerous, and even more so if one is intoxicated. Counting pedestrian deaths is hard, but reasonable estimates give nearly 900,000 pedestrians killed worldwide. If a car could tell whether it were heading for a pedestrian, it might be able to prevent an accident. As a result, there is much interest in building pedestrian detectors. The sliding window recipe applies naturally to pedestrian detection because pedestrians tend to take characteristic configurations. Standing pedestrians look like lollipops, and walking pedestrians have a quite characteristic scissors appearance. Dalal and Triggs invented HOG features for this purpose, and used a linear SVM to classify windows, because it is as good as the best classifier, but simpler. Another advantage of a linear SVM is that one can get some insight into what features are distinctive. Evaluating sliding window methods can be difficult. They advocate plotting the detection rate (percentage of true positives detected) against the false positives per window (FPPW). When evaluating these plots, it is important to keep in mind that they characterize the behaviour of the classifier, rather than the whole system. This is attractive if you are interested in features and classifiers, but perhaps less so if you are interested in systems. A higher FPPW rate may be tolerable if you have to look at fewer windows, though looking at fewer windows might affect the detect rate. Dollar et al have conducted a systematic evaluation of pedestrian detectors on a large dataset built for that purpose. The ranking of methods changes depending on whether one plots FPPW or false positive per image (FPPI); generally, we expect that FPPI is more predictive of performance in applications.

Our sliding window recipe has one important fault: it assumes that windows are independent. In pedestrian detection applications, windows aren't really independent, because pedestrians are all about the same size, have their feet on or close to the ground, and are usually seen outdoors, where the ground is a plane. If we knew the horizon of the ground plane and the height of the camera above that ground plane, then many windows could not be legitimate pedestrians. Windows whose base is above the horizon would be suspect because they would imply pedestrians in the air; windows whose base is closer to the horizon should be smaller. The height of the camera above the ground plane matters because in this problem there is an absolute scale, given by the average height of a pedestrian. Assume the horizon is in the centre of the image. Then, for cameras that are higher above the ground plane, legitimate pedestrian windows get smaller more quickly as their base approaches the horizon. There are two strong sources of information about the horizon and the camera height. First, the textures of the ground, buildings, and sky are all different, and these can be used to make a rough decomposition of the image that suggests the horizon. Second, observing some reliable detection responses should give us clues to where the horizon lies, and how high the focal point is above the ground plane. Show that these global geometric cues can be used to improve the behaviour of pedestrian and car detectors

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. Martin, who pioneered the method, call these maps the probability of boundary, for probability of boundary. For this problem, it makes sense to work with circular windows. Boundaries are oriented, so we will need to search over orientations. Each oriented window can be visualized as a circle cut in half by a line through the centre. If this line is an object boundary, we expect substantial differences between the two sides, and so features will compare these sides. Martin et al. build features for a set of properties (raw image intensity, oriented energy, brightness gradient, colour gradient, raw texture gradient, and localized texture gradient) by taking a histogram representing that property for each side, then computing the distance between the histograms. This means that each feature encodes the tendency of a particular property to look different on the two sides of the circle. This set of features is then supplied to logistic regression. The boundary detector is trained using images whose boundaries have been marked by humans. Human annotators don't get boundaries perfectly right. This means that the training dataset might contain multiple copies of the same window with different annotations some humans marked the point a boundary point, and others didn't. However, the set of windows is very large, so that such inconsistencies should be averaged out in training. The procedure we have described can be used to build two methods. One reports Pb(x, y, θ), that is, the probability the point is a boundary point as a function of position and orientation; the other reports. The second is most widely used. Testing requires some care, because reporting a boundary point close to, but not on, a boundary point marked by a human is not a failure. Martin cope with this issue by building a weighted matching between the boundary points marked by a human and those predicted by the method. Weights depend on distance, with larger distances being more unfavourable. A predicted boundary point too far away from any human-marked point is a false positive. Similarly, if there are no boundary points predicted close enough to a human-marked point, then that point counts as a false negative. We can then threshold the probability of boundary map at some value, and compute recall and precision of the method; by varying the threshold, we get a recall-precision curve. Although this method doesn't perform as well as humans, who can use context and object identity cues it significantly outperforms other methods for finding boundaries. 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 ensure that object boundaries are closed curves. You can see this as a method to force windows not to be independent.

Evaluation of object detection algorithms is a non-trivial task: a detection result is usually evaluated by comparing the bounding box of the detected object with the bounding box of the ground truth object. The commonly used precision and recall measures are computed from the overlap area of these two rectangles. However, these measures have several drawbacks: they don't give intuitive information about the proportion of the correctly detected objects and the number of false alarms, and they cannot be accumulated across multiple images without creating ambiguity in their interpretation. Furthermore, quantitative and qualitative evaluation is often mixed resulting in ambiguous measures.

In this, we propose a new approach which tackles these problems. The performance of a detection algorithm is illustrated intuitively by performance graphs which present object level precision and recall depending on constraints on detection quality. In order to compare different detection algorithms, a representative single performance value is computed from the graphs. The influence of the test database on the detection performance is illustrated by performance/ generality graphs. The evaluation method can be applied to different types of object detection algorithms. The introduction of the evaluation problem coincides largely with the emergence of the field of visual information retrieval. As a consequence, the first techniques have been naturally inspired by tools from this domain, as for instance precision/recall graphs which are frequently used in information retrieval. However, visual information has its own specificities, which need to be taken into account. This is the goal of this work.

Often it is necessary to conceive non-trivial algorithms in order to ensure an evaluation satisfying scientific requirements:

• A simple and intuitive interpretation of the obtained measures.

• An objective comparison between the different algorithms to evaluate.

• A good correspondence between the obtained measures and the objective performance of the algorithm to evaluate, taking into account its goal.

However, although the two evaluation problems may be similar from a theoretical viewpoint, practically *we need to emphasize some differences between page segmentation and text/object detection:*

• The density of relevant information is higher for page segmentation problems. In text detection, on the other hand, text areas are not so much “classified” as “detected”, i.e. that there can be and will be large areas which do not contain relevant material. This difference results in different evaluation techniques, which differ for instance in the way how the algorithms treat detection quality and detection quantity.

• In the page segmentation context, regions are possibly non-rectangular. The proposed evaluation algorithm, based on a rectangle representation of object reasons, is not applicable in this case.

The second point restricts the proposed evaluation systems to objects which are well represented by rectangles, which is the case for text, faces, people, generally speaking, compound objects. While the general philosophy of the proposed system is applicable, i.e., the separation of detection quality and quantity and its representation as graphs, the object matching part itself is restricted to rectangle based representations.

This paper presents a general, trainable system for object detection in unconstrained, cluttered scenes. The system derives much of its power from a representation that describes an object class in terms of an over the complete dictionary of local, oriented, multiscale intensity differences between adjacent regions, efficiently computable as a Haar wavelet transform. This example-based learning approach implicitly derives a model of an object class by training a support vector machine classifier using a large set of positive and negative examples. We present results on the face, people, and car detection tasks using the same architecture. In addition, we quantify how the representation affects detection performance by considering several alternate representations including pixels and principal components.

The problem of object and pattern detection in static images of unconstrained, cluttered scenes. We contrast detection with the problem of recognition, where the goal is to identify specific instances of a class. A face detection system knows how to differentiate faces from “everything else”, while a face recognition system knows the difference between my face and other faces. The detection of real-world objects of interest, such as faces, people, and cars, poses challenging problems: these objects are difficult to model with significant variations in colour and texture, the backgrounds against which the objects lie are often complex and cluttered, and characteristics like lighting, size, and number of objects cannot be accounted for in any but the most contrived situations.

Technique uses a descriptive model of the object class that is enough to model any of the possible poses, shapes, colour and textures of an object. We will be using an example-based learning approach where a model of an object class is derived implicitly from a training set of examples. In this way, specializing this general system to a specific domain involves plugging in a new set of training data without modifying the core system or handcrafting a model. The specific learning engine we use is a support vector machine (SVM) classifier.

This characterization system has various properties that make it especially attractive and has recently received much attention in the machine learning community. In the testing phase, we are interested in detecting objects in out-of-sample images. The system slides a fixed size window over an image and uses the trained classifier to decide which patterns show the objects of interest. At each window position, we extract the same set of features as in the training step and feed them into our classifier; the classifier output determines whether or not we highlight that pattern as an in-class object. To achieve multiscale detection, we iteratively resize the image and process each image size using the same fixed size window.

We present an approach for learning to detect objects still grey images that are based on a sparse, part-based representation of objects. A vocabulary of information-rich object parts is automatically constructed from a set of sample images of the object class of interest. Images are then represented using parts from this vocabulary, along with spatial relations observed among them. Based on this representation, a feature-efficient learning algorithm is used to learn to detect instances of the object class.

We report experiments on images of side views of cars. Our experiments show that the method achieves high detection accuracy on a difficult test set of real-world images, and is highly robust to partial occlusion and background variation. In addition, we discuss and offer solutions to several methodological issues that are significant for the research community to be able to evaluate object detection approaches.

The approach presented is based on the belief that the key to finding a solution to this problem lies in finding the right representation. Specifically, we suggest that in order to extract high-level, conceptual information such as the presence of an object in an image, it is essential to transform the raw, low-level input (in this case, the pixel grayscale values) to a higher-level, more “meaningful” representation that can support the detection process. We describe the approach that uses an automatically acquired sparse part based representation of the object to learn to detect the occurrences of objects in natural sciences. The method is highly robust to jumbled backgrounds and partial occlusion. Our goal is to develop a system which, given an image, can detect instances of this object class in the image, and return their locations. In the process of finding the locations of these object instances, we also require the system to be able to output the number of object instances it finds in the image. This may appear to be a trivial requirement for an object detection system. To exploit both local image data as well as contextual information, we introduce Boosted Random Fields (BRFs), which uses Boosting to learn the graph structure and local evidence of a conditional random field (CRF). The graph structure is learned by assembling graph fragments in an additive model.

The connections between individual pixels are not very informative, but by using dense graphs, we can pool information from large regions of the image; dense models also support the efficient inference. We show how contextual information from other objects can improve detection performance, both in terms of accuracy and speed, by using a computational cascade.

Boosting is a simple way of sequentially constructing “strong” classifiers from “weak” components, and has been used for single class object detection with great success. In addition to recognizing things, such as cars and people, we are also interested in recognizing spatially extended “stuff”, such as roads and buildings. The traditional sliding window approach to object detection does not work well for detecting “stuff”. Instead, we combine object detection and image segmentation by labelling every pixel in the image. We do not rely on a bottom-up image segmentation algorithm, which can be fragile without top-down guidance.

The proposed BRF algorithm combines boosting and CRF’s, providing an algorithm that is easy for both training and inference. We have demonstrated object detection in jumbled scenes by exploiting contextual relationships between objects. The BRF algorithm is computationally efficient and provides a natural extension of the cascade of classifiers by integrating evidence from other objects in order to quickly reject certain image regions. The BRF’s densely connected graphs, which efficiently collect information over large image regions, provide an alternative framework to nearest-neighbour grids for vision problems.

Methods that are proposed by some scientists for counting cells

[1]. Xiaomin Guo and Feihong Yu introduced a method of automatic cell counting based on microscopic images. Histogram information is used to calculate adjustable lower and upper threshold value. This value is used for segmentation of objects and background. Effect of Flood fill method fills the objects region. It is used to mark or separate regions in an image. A blob is an area of touching pixels with the same logical state. All pixels in an image that belong to a blob are in a foreground state. All other pixels are in a background state. Blob analysis is used to detect blobs in an image and make selected measurements of those blobs. Blob analysis consists of a series of processing operations and analysis functions that produce information about any 2D shape in an image. If size of a blob is beyond the upper threshold of area, the blob will be segmented by K-means clustering algorithm. By calculating the number of cells contained in each blob obtains the total number of cells in whole image. The result shows that maximum relative error is 1.33%, minimum relative error is 0% and the average relative error is 0.46%.

[2]. Venkatalakshmi. B et al. presented a method for automatic red blood cell counting using hough transform. The algorithm for estimating the red blood cells consists of five major steps: input image acquisition, pre-processing, segmentation, feature extraction and counting. In pre-processing step, original blood smear is converted into HSV image. As Saturation image clearly shows the bright components, it is further used for analysis. First step of segmentation is to find out lower and upper threshold from histogram information. Saturation image is then divided into two binary images based on this information. Morphological area closing is applied to lower pixel value image and morphological dilation and area closing is applied to higher pixel value image. Morphological XOR operation is applied to two binary images and circular hough transform is applied to extract RBCs.

[3]. J.N. Fabic et al. described an efficient method for fish detection, counting and species classification from underwater video sequences using blob counting and shape analysis. The proposed system is consists of four major steps: Pre-processing, Contour detection, Blob Counting and Species Identification. Preprocessing is done for cleaning the background by eliminating unwanted objects. It involves Coral Blackening Procedure to blacken out corals using colour histogram, Inward-Outer Block Erasure Algorithm to distinguish between fish and water and Edge Cleaning Algorithms for clearly defining edges. Contour Detection utilizes the canny edge

detection to detect fish contours and fill up spaces to allow blob counting. The blob detector is based on Laplacian of Gaussian (LoG). Connected components algorithm is used to label connected regions in binary images and subsets can be uniquely extracted. These results are used for counting, filtering or tracking. Species identification is done with the help of image moment features of the blob. From results, it is observed that the tolerance is less than 10 %.

[4]. Haider Adnan Khan et al. presented a framework for cell segmentation and counting by detection of cell centroids in microscopic images. Preprocessing is done with Contrast-Limited Adaptive Histogram Equalization to get enhanced image. Next, cells are separated from background using global thresholding. Then, distance transform of binary image is computed which converts binary image into distance map indicating distance of every cell pixel from its nearest background pixel. In order to perform template matching, the template image is generated from the distance transform of circular disk. Distance map is used to identify the cell centroids. The template matching is done using normalized cross-correlation between template and distance map. Finally, the similarity matrix is complemented and all background pixels are set to minus infinity. The watershed transform is then applied on this complemented similarity matrix. This splits the similarity matrix into separate disjoint regions. Each region is labelled and counted to get the count. The experimental results show excellent accuracy of 92 % for cell counting even at very high 60 % probability.

[5]. Watcharin et al. proposed an algorithm to count blood cells in urine sediment using ANN and hough transform. First step of algorithm is the segmentation between background and blood cells by using feed forward back propagation algorithm. For training neural network, the input is Hue, Saturation, Value and standard deviation. After deriving output from feed forward back propagation, salt and pepper noise is eliminated by using morphological opening and closing method. Last step is blood cell counting using circular hough transform. Experimental results show the average percentage of error of RBCs and WBCs detection 5.28 and 8.35 respectively.

[6]. J. G. A. Barbedo presented a method for counting of microorganisms that use a series of morphological operations to create a representation in which objects of interest are easily isolated and counted. First step of this method is RGB to grey conversion. After that, two-dimensional median filter is applied, in order to eliminate noise and other artifacts. Ideal size of the neighbourhood over which filter should be applied depends on three main factors: size of objects of interest, size of spurious artifacts and resolution of the image. The program has two approaches for deciding neighbourhood. In the first approach, user enters estimate of diameter of objects and artifacts. In the second approach, estimation using multiple counts is done. Then, contrast is adjusted in such a way the brightest pixel assumes the full-scale value 255 and darkest pixel equal to zero. In following, the algorithm verifies if the background is brighter or darker than the objects. If the background is brighter, a complement operation is performed. The image is then submitted to top-hat morphological filtering. Image is binarized with threshold in 128. After that object counting becomes trivial. By observing results, it can be seen that, except for the case of merged objects, the method identifies the objects correctly in more than 90 % of the cases, and the number of false positives is always low. The overall deviation was 8 %; such a number falls to 2.5 % if the images with merged objects are not taken into account.

[7]. Marjan Ramin et al. used image analysis technique for counting number of cells in Immunocyto chemical (ICC) images. The proposed system contains four major steps: Pre-processing, Classification, Separating Bound Nucleus and Cell Counting. Pre-processing consists of removal of random noise by smoothening spatial filter. Morphological open operator is utilized to eliminate images' background. Banding noise is removed by subtracting median of the red channel from all channels. In order to separate nucleus from antigens, nearest neighbour classification method with Euclidean distance metric is used in L*a*b colour space. The bound nucleus is separated by local thresholding algorithm. For this purpose, statistical analysis is done and optimal threshold is found with the help of genetic algorithm. Finally, cell counting is done by tracing the boundaries. From the results, the Error Ratio and Standard Deviation of the proposed method are 6.75% and 6.39% respectively.

[8]. Carlos A. B. Mello et al. presented two methods for mosquito eggs counting. These methods are based on a different colour model. In the first method, RGB image is converted into HSL colour model (Hue, saturation, Lightness). From these three components, the hue image is extracted as it contains information about colour tone. Huang thresholding algorithm is applied to the hue image for binarization. A connected components algorithm is used to label the connected regions of the image. Filtering is done using morphological opening operation with structuring element defined in the form of egg. At the last step, it is considered that egg occupies area of 170 pixels. The number of eggs is calculated by dividing the total amount of white pixels by this average area. The second method is based on converting RGB sub-image to YIQ one. From these components, I band is segmented in two ways: by using limiarization with fix threshold of 200 and by binarization using k-means clustering method. For performing egg counting in this method, it is considered that the average size of mosquito egg is 220 pixels.

AUTOMATION OF COUNTING OBJECTS IN AN IMAGE USING IMAGE PROCESSING TECHNIQUES

IV. SURVEY TABLE

S.no	Paper name	Author	Techniques	Drawbacks
1	Learning to count objects in images. In Advances in Neural Information Processing Systems	Lempitsky, V., & Zisserman, A	The counting-by-detection baseline. Application-specific method.	
2	Counting crowded moving objects. In Computer Vision and Pattern Recognition,	Rabaud, V., & Belongie, S	The proposed density-based approach. The counting-by-regression baseline.	Expensive and sophisticated equipment used
3	In Advances in neural information processing systems	Floeder, S. P., Graessle, J. A.,	***petri dishes***	The petri dishes be illuminated through their bottom surface which requires a substrate which is light permeable to ensure accurate counting.
4	Technique to count objects in a scanned image	Floeder, Steven P., et al		
5	A technique to count objects in a scanned image & Biotechnology Advances	Floeder, S., Graessle, J.,	A method of counting microbial colonies growing in a solid medium	
6	Object count/area graphs for the evaluation of object detection and segmentation algorithms	Wolf, C., & Jolion, J. M.		
7	Learning a sparse representation for object detection. In European conference on computer vision	Papageorgiou, C., & Poggio, T	boundary detection	
8	Contextual models for object detection using boosted random fields. In Advances in neural information processing systems	Torralba, A., Murphy,K. P., & Freeman	BRF algorithm	

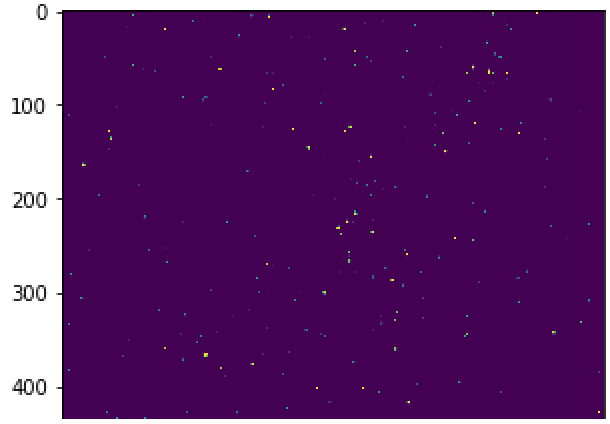
Summary

The main contribution of this paper concerns the following issues:

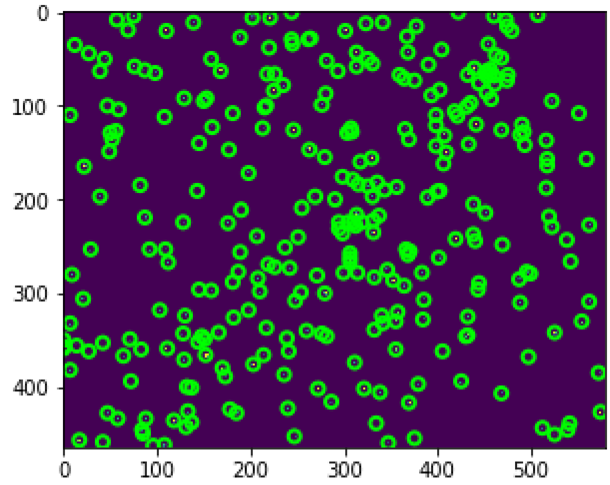
- The separation of detection quality and detection quantity. New performance graphs allow us to easily perceive the detection quantity ("how many objects have been detected?" and "how many false alarms have been detected?") as well as detection quality ("how accurate is the detection of the objects?").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

V. Result Analysis

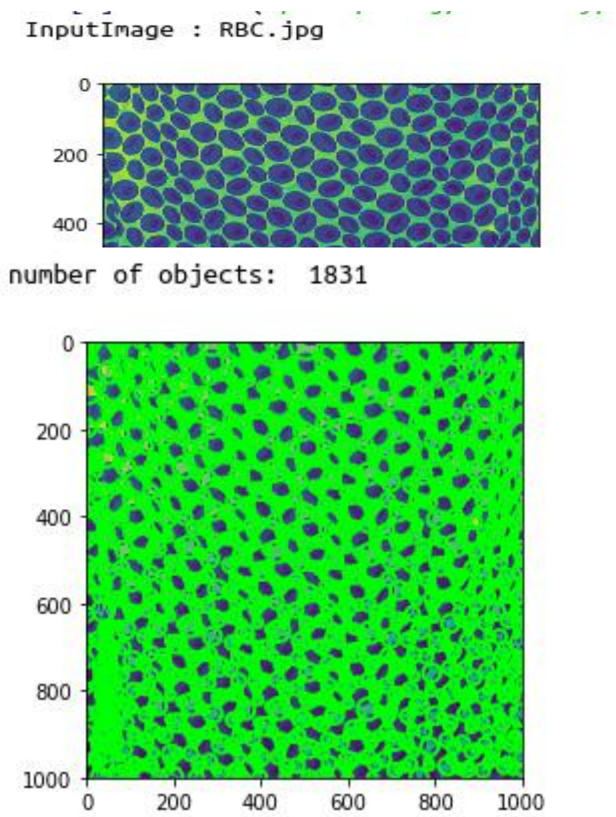
InputImage : stares.png



number of objects: 298



AUTOMATION OF COUNTING OBJECTS IN AN IMAGE USING IMAGE PROCESSING TECHNIQUES



VI. Conclusion

We came to a conclusion that we can recognize only one language at a time and that too off-line handwriting recognition is very hard because handwriting differs from person to person. Some papers or techniques recognize two language numerals but not words. Most of the papers used Hidden Markoivan Model in their method of recognition of handwriting. Some many research is going on this off-line handwriting recognition. Even though none of the models was able to recognize with 100% accuracy rate. Among all the papers only one paper is giving 99.76% accuracy rate in the handwriting recognition and in this Crack codes and Fourier Descriptors method is used.

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