A Study on the Use of Semi-Automatic Systems for Counting Objects in Digital Images

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Abstract— **This paper presents an investigation on the impact of coupling a manual correction module to automatic methods for counting objects in digital images, effectively turning them into semi-automatic systems. This study aims to show that completely automatic counting methods often cannot achieve enough accuracy for certain applications and under certain conditions, and that in many cases the introduction of manual corrections is advantageous, despite the impact of this on the time spent by the whole counting process. The paper presents a thorough comparison between fully automatic, fully manual and semi-automatic approaches, using images containing a variety of objects and characteristics, so those approaches could be tested under a wide range of conditions, from the simpler one to the most challenging. It is shown that, with the exception of a few specific situations, the semi-automatic approach is advantageous over the manual counting in terms of time, and over the automatic counting in terms of accuracy. The situations in which the automatic or manual approaches should be preferred are also described.**

Keywords-object counting, digital images, semi-automatic systems.

I. INTRODUCTION

Counting objects is an activity that is routinely carried out in companies, research institutes, laboratories, among others. In many cases, the count is performed manually, in a process that can be both lengthy, tiresome and, as a consequence, error prone. Because of that, many different methods for automatic counting objects have been proposed in the last two decades. Some areas that have received attention on the matter are the counting of cells [1]-[4], bacteria colonies [5]-[9], trees [10]-[13], insects [14]-[17], fruits [18]-[19], pollen [20]-[21], ears [22]-[23], seeds [24]-[25], and root nodules [26]-[27].

The problem with those entirely automatic methods is that they usually are developed under very tight constraints regarding imaging conditions and type of objects. Additionally, their accuracies may not meet the requirements of the more demanding applications. A possible intermediate solution would be the so-called semi-automatic methods, which still automate most of the process, but need the input of human users in order to refine their estimates. In fact, any automatic method, including those cited above, can easily be coupled with a manual correction module, then becoming a semi-automatic system. This kind of approach is very common in many image processing applications, but has not yet been properly explored in the context of object counting.

The main contribution of this paper is the description of the results of several experiments designed specifically to determine when the semi-automatic approach is more appropriate. A summary of the discussions detailed in Section III is presented in the following:

- The manual counting approach should be used in situations for which automatic methods fail so completely that the manual corrections would take more time than simply counting the objects by hand. This is not a very common situation, but it may happen when the image is extremely noisy, when the objects to be counted are amidst several other types of objects, when the objects are extremely clumped, or when the contrast between objects and background is extremely low.

- The fully automatic approach should be preferred in two situations. First, if the capture the images is so tightly controlled that there is little or no variation of characteristics from image to image. In this case, it is often possible to create a fully automated system capable of consistently providing accurate estimates. Second, if time is a more pressing issue than accuracy, in which case errors may be tolerated as a trade off for having the results available in a timely fashion. This situation is particularly common if a large number of images are to be processed, because in this case an automatic method is usually capable of processing all images in a single batch, while the manual correction requires that the images be considered one by one.

- The semi-automatic approach will be appropriate in all situations that do not fit the conditions described above. In other words, this kind of approach should be preferred when accuracy prevails over speed as the most important factor, the automatic part of the system is capable of providing minimally accurate estimates, and the image conditions vary. The large majority of counting problems will fit these conditions.

Next section presents a more detailed characterization of each kind of approach.

II. Characterization of the Approaches

A. Manual Approach

The techniques used for manual counting of objects may vary greatly, but most of them have some common basic characteristics. Some examples of counting procedures:

- Sheet of paper: in this case, an image of the objects is captured and printed out into a sheet of paper. If there are many objects, it is common to use some kind of marker, like a pen, to highlight the object that have been already counted.

- Glass dish: this procedure is very common for counting bacteria colonies. In this case, the objects are counted directly where they lie and, if necessary, the objects already considered are highlighted by a mark made on the glass covering the dish.

- Direct: if the objects are solid and macroscopic, they may be counted directly. This is the case, for example, for seeds and grains. In this case, the objects already considered are simply separated from the uncounted group.

In all of those cases, it is common to use of a hand counter to keep track and store the values, especially if there are many objects.

The time required to perform a manual count depends not only on the number of objects, but also on the proficiency of the person appointed to perform the task, and also on the way the objects compare with the background - the more contrasting they are, the faster is the counting.

It is important to highlight that, although the results provided by the manual counting are usually taken as the target to be pursued by automatic approaches, it is not error free. In fact, there are many factors that can lead to error, like distractions, fatigue, misidentifications, among others. As a result, there is no ground truth that could be used to assess the performance of automatic and semi-automatic methods. What is done instead is to find the correlation between automatic and manual counting - the higher is such a correlation, the better the automatic method is considered to be.

B. Automatic Approach

As in the case of manual counting, automatic methods can vary greatly, and they also have some characteristics in common. The main advantages and disadvantages of this kind of approach is presented in the following.

Advantages:

- Automatic methods tend to be very fast. Most methods use very light image processing techniques, and even when more sophisticated and computationally demanding techniques are used, the evolution of computational power quickly make those comparatively fast. Possible exceptions may occur when the images have extremely high resolution, which may stretch the memory resources beyond reasonable levels.

- Automatic methods have batch processing capability. With this kind of approach, it is possible to feed the program with a large number of images at once, leaving the user free to perform other activities.

- Automatic methods are not subject to cognitive flaws. A computer program does not suffer from fatigue and cannot be distracted. In fact, a perfect algorithm would always lead to the best possible estimate for the number of objects, thus making this kind of approach the most adequate. Unfortunately, perfect algorithms are currently unfeasible, so errors inherent to algorithmic flaws will always be present.

Disadvantages:

- Automatic methods tend to be more constrained. Virtually all the methods proposed in the literature are developed having a very specific application in mind, so they lack any kind of generality. More importantly, many of those methods only work properly under very specific conditions regarding the imaging process, that is, factors like angle of the capture, lighting, distance between sensor and objects, among others, must be tightly controlled.

- Automatic methods may not meet the accuracy required by some applications. In some cases, the accuracy required for the estimate of the number of objects is very high. Due to flaws inherent to the methods and the impossibility, in some cases, of generating images that meet the method's constraints, such an accuracy may not be met.

C. Semi-Automatic Approach

Semi-automatic systems combine automatic processing with manual tunings or corrections. The interaction with the user may include explicit tuning of parameters used by the automatic part of the system, like the size of filter kernels, the threshold used in the image binarization, the smallest size accepted for an object, among others. Although this is an interesting way for the user to improve the accuracy of the estimates, it is very difficult to analyze, in a quantitative way, the impact of those interactions, especially in terms of time spent. Also, it may not be simple, or even possible, to introduce this kind of user interaction into the framework of most automatic counting method. For those reasons, this work concentrated its efforts on studying the most straightforward user interaction, which is the direct manual correction of the estimated results. Next section presents the tests performed to determine the impact of coupling this manual correction with automatic counting methods.

III. Tests and Results

A. Setup

A total of 23 images were used in the tests, with some examples shown in Fig. 1. Those images were selected to cover as many practical situations as possible, with emphasis on agricultural scenes. Those images were stored using the JPEG file format and the RGB (Red-Green-Blue) color space. Because of the wide variety of the images, statistical information about them, like power spectra and histograms, will be omitted.

The manual counts were performed by four individuals that were trained prior to the analysis of each image, so they would count the right objects. Ideally, the counts should be performed

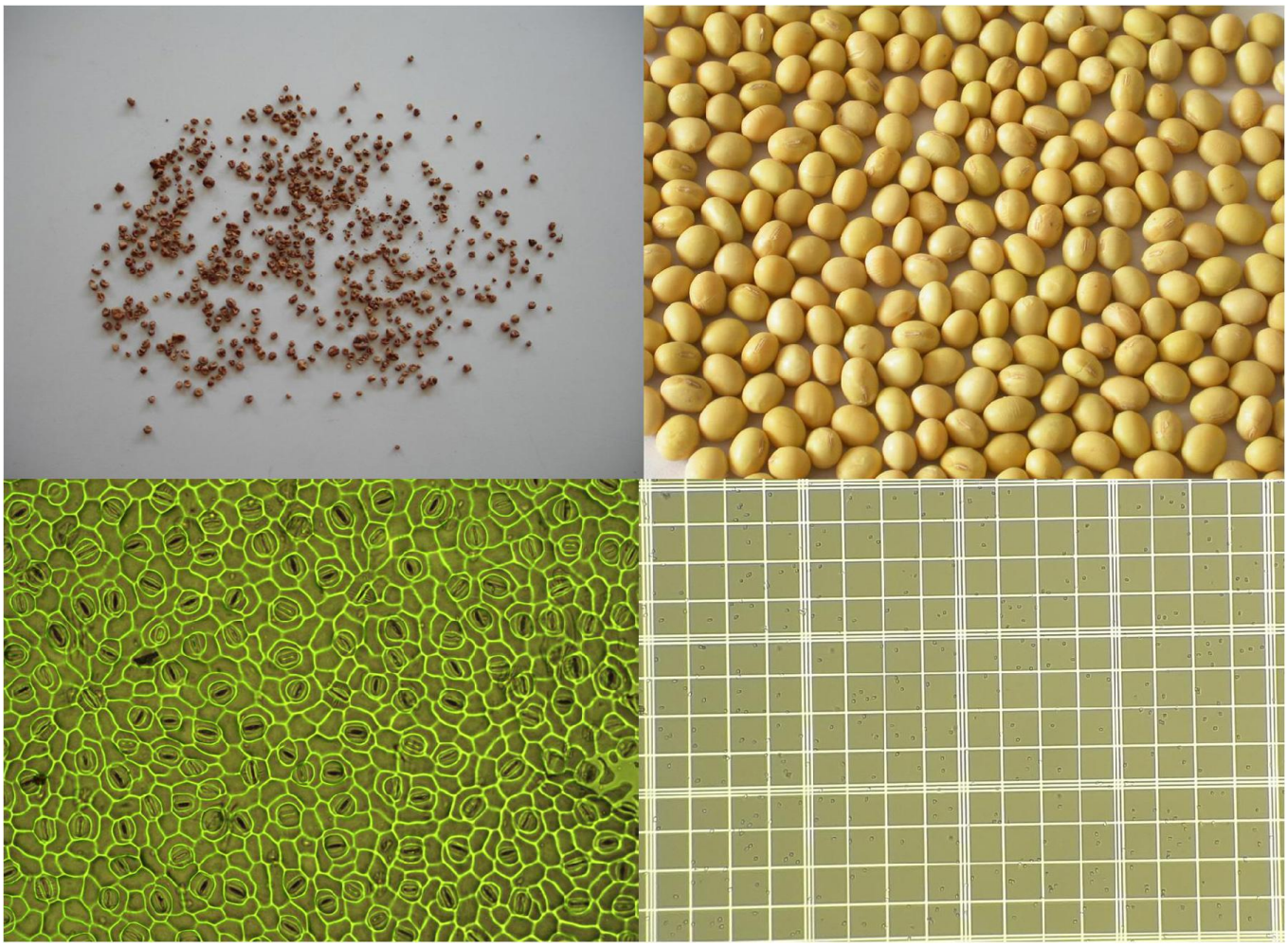

Figure 1. Examples of images used in the tests.

by experts on the subject of each image, however this would be unpractical due to the amount and variety of images. The manual counts were performed using a high quality printed version of the images, and every counted object would be marked with a pen.

The images to be corrected were not generated by an actual automatic method. Instead, the markings that identify the objects were inserted manually, so the number of false positives and missed objects could be tightly controlled. This does not influence the results presented in the following, as the evaluation of the automatic part of the system was not part of the scope of this paper.

The correction system used in this work is very simple. The objects detected by the automatic part of the system (here manually inserted, as commented above) are marked on the image, and the user may include new points by pressing the left mouse button over the undetected object, and also remove spurious objects by clicking on it with the right mouse button. Fig. 2 shows an example of the correction process. As can be seen in the left image, the identified objects were marked with red circles, but some objects were not detected by the algorithm and some spurious detections also occurred. In the right image, the user was able to identify and mark undetected objects (green circles), and also removed spurious ones (black circles).

In the comparison between the manual and semi-automatic counting approaches, the time required for the automatic method to process the image was assumed to be negligible when compared with the manual part of the process, which is true for most automatic methods proposed so far. For example, the methods presented in [9] and [25], implemented in C++, took about 2 seconds to process 10-Megapixel images using the computational power available at the time of this research (2013). This time can be further reduced if the code is implemented to use GPU (Graphical Processing Unit). As a consequence, the comparison is actually between the time required to perform the count manually and the time required to perform the corrections.

Due to the several factors involved in such a comparison, designing tests capable of providing a complete picture is not a trivial task. In the end, several comparisons were performed, each considering a different aspect of the problem.

B. First Experiment: Missing Objects

The first experiment tested how much time would take to

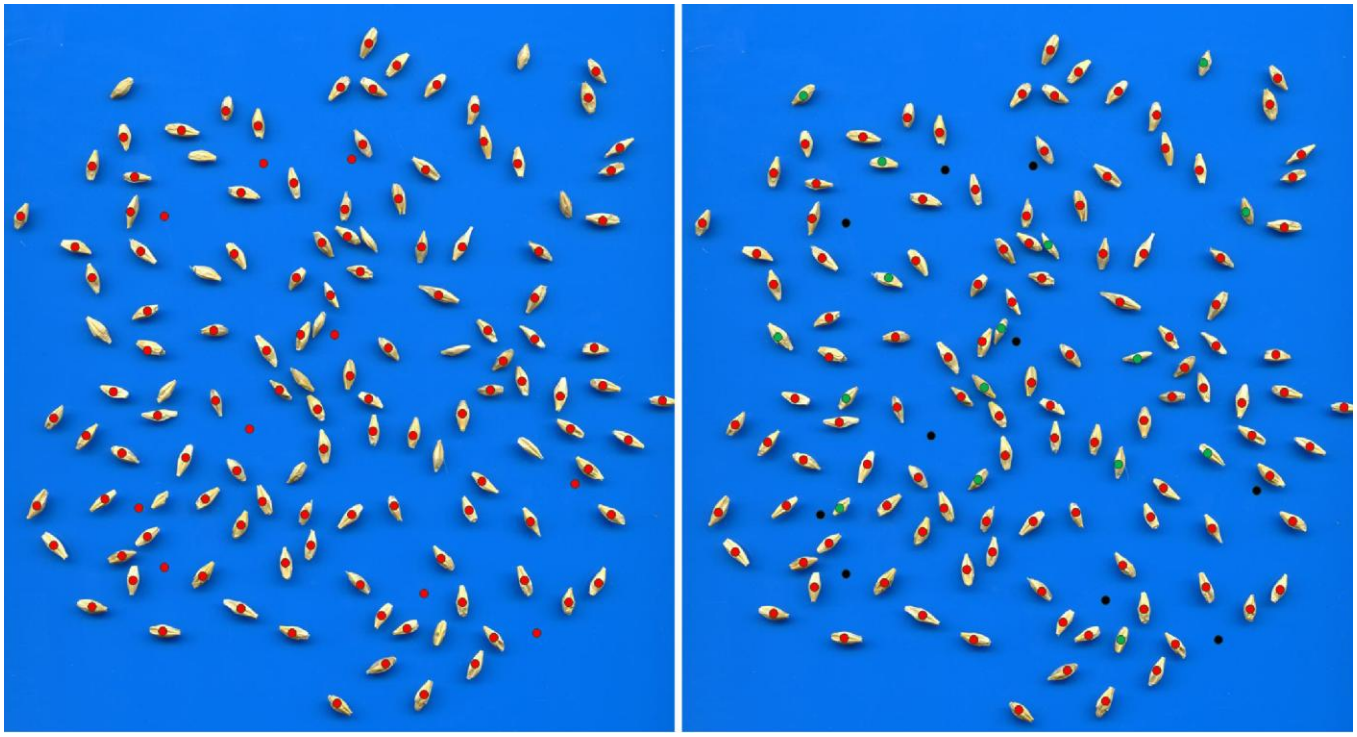

Figure 2. Example of the correction system.

identify missed objects in the image. Fig. 3 shows how such a time varies as the percentage of missed objects grows (horizontal axis), in terms of the ratio between correction and manual times (vertical axis). Values below one in the vertical axis indicate that the time taken to correct the estimates is smaller than the time taken for manually count the objects. As can be seen, the time ratio between corrections and manual count varies almost linearly, which was expected. It is also worth noting that when no object was detected (100%), in which case the correction process is equivalent to a purely manual count, the semi-automatic approach still was slightly faster than the manual count. This indicates that the correction system adopted here is more time-effective than using a sheet of paper to perform the count. The results shown in Fig. 3 are an average over all individuals and all images used here; some remarks about how the object type and characteristics influence the results are presented later in this section.

C. Second Experiment: False Positives

The second experiment focused on the correction of false positives, as shown in Fig. 4. In the images submitted for manual corrections, all actual objects were correctly identified, together with some false positives. The number of false positives with respect to the actual number of objects (in %) is presented in the horizontal axis of Fig. 4. Since the number of false positives can be larger than the number of actual objects, the percentage of false positives can be larger than 100%.

As can be seen, the larger the number of false positives, the faster the correction time/manual count time ratio grows. This is mainly because false positives cause the image to become very busy, as those are extra elements beside the actual objects. As their number grows, more attention and effort is necessary to identify and purge them, which slows down the whole process. In average, it was observed that, if the total number of false positives is larger than 70% of the number of objects, manual counting is more appropriate. If there are also missing objects to be corrected, then this number is lower. For the semi-automatic approach to be advantageous over the manual count, considering the images used here, the following inequality should hold: $0.96 \cdot MO + 1.37 \cdot FP < 1$, where MO is the number of missed objects divided by the number of actual objects, and FP is the number of false positives divided by the number of actual objects. It is important to notice that, under certain difficult conditions, that inequality may not be valid, as will be seen in Section III.E.

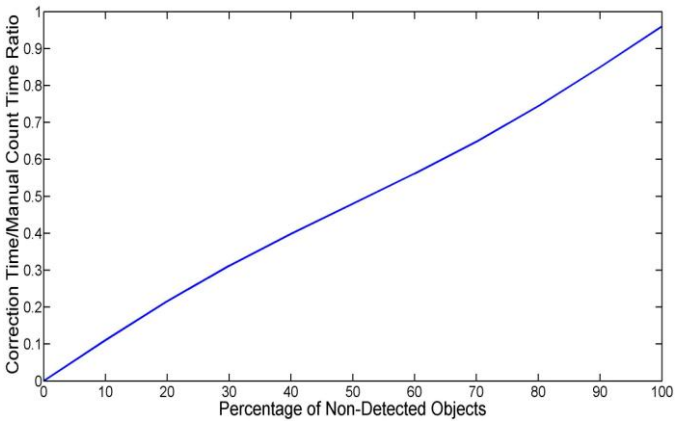

Figure 3. Comparison between manual and semi-automatic count approaches - missed objects.

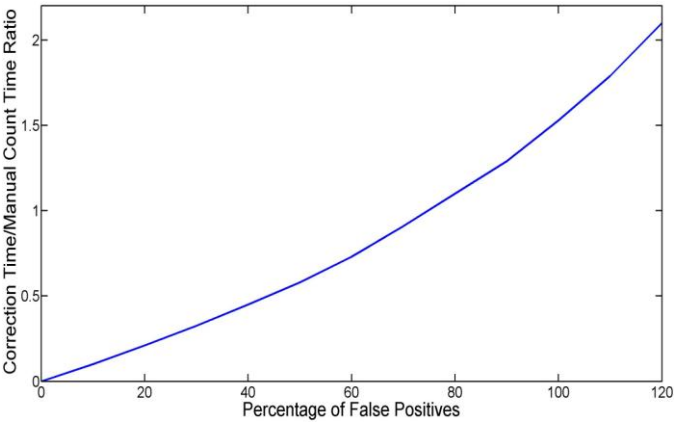

Figure 4. Comparison between manual and semi-automatic count approaches - false positives.

D. *Third Experiment: Comparison Between Errors*

The third experiment aimed to determine what happens when both types of errors are present. Fig. 5 was generated fixing the overall number of errors (70% of the number of objects), and varying the percentage of false positives. As a result, the value 0 in the horizontal axis indicate that all errors are due to missed objects, and 1 indicates that all errors are due to false positives. As expected, as the proportion of false positives grows, the time necessary to correct the errors also grows.

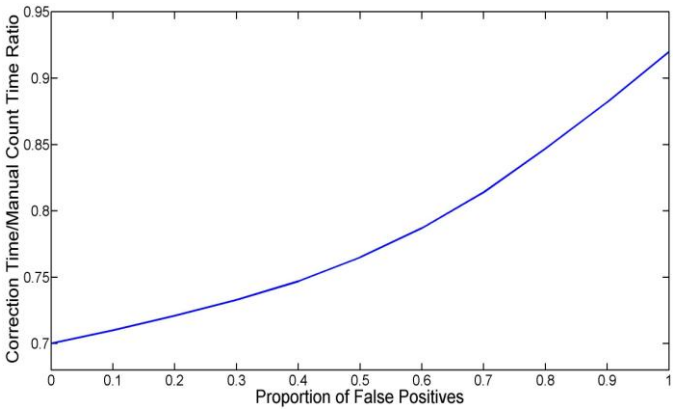

Figure 5. Comparison between manual and semi-automatic count approaches when both types of error are present.

E. *Problematic Cases*

As commented before, the characteristics of the objects may influence the time and difficulty involved on the corrections. Some of the most important factors are discussed below.

In the case of size, if the objects are very small, the very markings that indicate if an object was identified or not by the automatic part of the system may occlude the object, making it difficult for the user to determine if that is a hit or a false positive. This, in turn, may cause the correction process to become extremely slow, rendering the system virtually useless. In cases like this, it may be better to use some other type of marking, for example a hollow circle encompassing the objects. Small objects are also more likely to come in large numbers, in which case the image becomes very busy, also slowing down the correction process. On the other hand, since computers have resources like zooming in certain areas of the images, this problem may be mitigated.

Other kinds of problems may not have practical solutions, which can severely slowing down the correction process. In those cases, the manual approach may be the best choice. One of these more serious problems arise when the objects have low contrast with the background (Fig. 6a). In this case, the automatic part of the system is likely to fail, causing a large number of errors. Since this kind of situation makes it very difficult even for humans to identify the objects, it is often preferable to perform the manual counting over a clean image than trying to correct an image full of markings, many of them potentially wrong.

Another problematic case is when the objects are strongly clustered. If each object has some type of feature that helps distinguishing them from their neighbors, usually the automatic methods are capable of doing a good job, otherwise errors are likely to happen. If those clusters dominate the image, as in Fig. 6b, it is likely that humans will do a much better job identifying and counting the objects.

If the amount of noise in the image is excessive, the automatic counting methods will also have problems. Such a noise, which can originate from either problems in the capture or from debris, may be partially neutralized by filters, provided that the objects are large enough to not being filtered out in the process. If the objects are small, as shown in Fig. 6c, the noise may interfere in the detection stage, causing a number of errors so high that a purely manual count becomes more appropriate.

Problems may also arise when the object to be counted is only one kind among several types of objects (Fig. 6d). In some cases, the automatic methods are capable of identifying the correct objects, especially if those have distinctive characteristics. However, if the differences between different classes of objects are minor, the automatic part of the system may fail completely. On the other hand, humans have a remarkable ability of detecting small cues in images, making the manual count a better choice.

There are also some cases in which a fully automatic method is a better choice. If the automatic counting method was carefully designed to deal with a very specific case, and if the images are expected to be uniform and homogeneous, it is unlikely that corrections will be necessary often. In those cases, for the sake of speed, the correction action may be bypassed. Also, if speed is the most important factor, and particularly when a large number of images must be analyzed, a purely automatic approach must be preferred, provided that the accuracy expected to be achieved by the method meets the minimum requirements for that application.

IV. Conclusions

This paper presented a study on the use of semi-automatic systems for counting objects in digital images. In particular, it was considered the situation in which a human user corrects

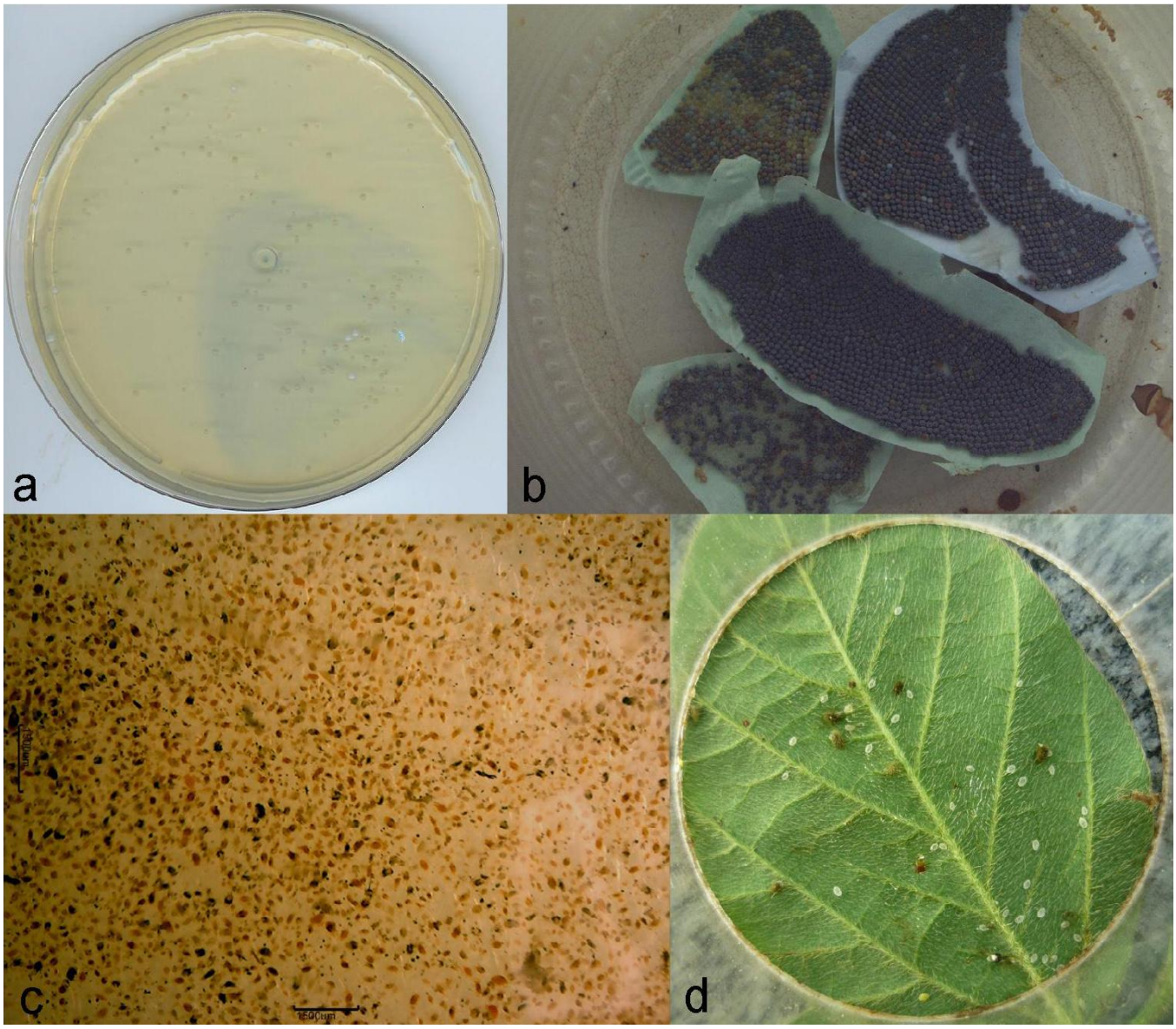

Figure 6. Problematic cases: a) Low contrast between objects and background; b) Heavy clustering; c) High noise levels; d) Several types of objects.

misestimates coming from the automatic part of the system. It was shown that, despite the additional time required for this correction, this kind of approach is still faster than purely manual counts in the vast majority of the cases, providing, at the same time, the same level of accuracy. It was also shown that correcting missing objects is easier and faster than correcting false positives. Finally, the paper discussed the cases in which a purely manual approach is more advantageous, namely when there is low contrast between objects and background, when there is heavy clustering, when the noise levels are too high, and when there are several types of objects in the image. On the other hand, purely automatic methods are preferable when speed is the most important factor and when several images are to be analyzed, provided that their accuracies meet minimum requirements.

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