Automatic Silkworm Egg Counting Mechanism for Sericulture

Rupali Kawade, Jyoti Sadalage, Rajveer Shastri and S. B. Deosarkar

Abstract Sericulture is an art of rearing silkworm for the production of cocoons, which is the raw material for the production of silk. The silkworm seed production is one of the important activities of sericulture in which the silkworm seed known as Disease Free Layings (DFLs) are prepared in their centers and supplied to the farmers for rearing. It is very important to count the number of silkworm eggs accurately so that farmers can pay accordingly and they should not suffer a loss. In order to generate some statistics, the fecundity and hatching percentage is measured by counting silkworm eggs. This counting is usually performed in a manual, visual, and non-automatic form, which is erroneous and time-consuming. This work approaches the development of automatic methods to count the number of silkworm eggs using image processing, particularly color segmentation and mathematical morphology.

Keywords Sericulture · DFLs · Image processing · Mathematical morphology

Introduction

No other fabric has fascinated man so continuously over millennia as silk. It is royal in its splendor, exotic, and sensuous in its radiance. Sericulture is essentially a village-based industry in which silkworms are reared for the production of

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cocoons. The cocoon is the raw material for the production of silk. India has the unique distinction of being the only country producing different kinds of silk. The larva of mulberry silk moth is a domesticated form which grows feeding mulberry leaves. The silkworm seed production is one of the important activities of sericulture in which DFLs are prepared in their centers known as grainages and supplied to the farmers for rearing. In sericulture, the demand of eggs for rearing silkworms is not uniform throughout the year. When seed cocoons are available in plenty of favorable seasons, surplus quantity of eggs are prepared and stored in cold storage to release at the time of demand [1].

In silk production, the number of silkworms required for a particular plantation of mulberry trees, should be approximate one for good yield of silk, so that mulberry leaves will not be wasted. For this farmers must purchase approximate number of eggs from grainages. Variability of egg quantities laid on sheets during production can cause economic losses. In addition quality control measures to monitor the egg numbers is tedious and laborious. While selling the silkworm eggs for rearing it is necessary to count the silkworm eggs accurately. This counting also determines the fecundity and hatching percentage of silkworm rearing.

The conventional method for the silkworm egg counting is by using ink/sketch pen. The transparent paper is put on the egg sheet and eggs from one DFL are counted by marking it using sketch pen. Each DFL approximately contains 450–550 eggs. Eggs from all DFLs on sheet are calculated by multiplying number of eggs from one DFL by total number of DFLs on sheet. This is usually performed manually which can be erroneous and time consuming. Karnataka State Sericulture Research and Development Institute, Bangalore (India) has implemented a calculator for egg counting. A simple pocket calculator is modified into a egg counter using small probe to count the silkworm eggs. The probe is attached to a pen, which will be pressed gently against each egg. As a result, the counted number will be marked and at the same time calculator will record the number. This avoids remembering of the counted egg number and concentrate only on marking. This improves the accuracy of counting and efficiency. This technology can be adopted in grainages, CRCs and seed a multiplication center which reduce the error during the egg counting and increases the quality parameters. The main disadvantage is that it puts the pressure on eggs because of which the embryo in an egg may get harm, and because of it the hatching efficiency decreases. This is also time-consuming [2].

Image processing techniques are being used frequently to count objects, orient pieces, or discriminate between objects with different visual characteristics. Most automated image systems perform counting by segmenting the object to be counted from background by applying a threshold based on the pixel intensity and/or intensity slope (or rate of change of intensities). Using this methodology, automated imaging systems have been developed to count mosquito eggs [3], [4], to count the objects in a video [5], to count number of feeder fish [6]. In addition, there are several commercial software programs that use this methodology to count objects given a digitized image. Pearson et al. have proposed method for counting insect eggs by image analysis [7]. Haouari and Chassery proposes a method to detect schistosome eggs in a microscopic environment connected to a computer. The advantage of this method is the use of a simple two pass algorithm. The first pass detects and analyses the elementary cases of isolated objects. The second pass introduces an enhancement process to improve the classification ratio [8]. Liao et al. have presented pelagic egg identification system by image analysis. Some efficient techniques have been developed such as the edge detection method using human visual characteristics, the improved Hough method for circle extraction and the embryo segmentation method [9]. These object counting systems can work well if the objects are only one layer thick and have good contrast from background. These algorithms are experimented for counting the silkworm eggs for sericulture.

This paper is organized as follows: next section describes the images acquired and the algorithms developed to perform automatic counting of silkworm eggs. In Section "Discussion and Result," the results are related and analyzed. Section "Conclusion and Future Scope" concludes and describes the future scope.

Materials and Methods

A digital camera with 12 megapixels resolution and 4.5 times optical zoom is used. The camera is connected to personal computer. A digital image captured from camera of size 1600 versus 1,200 pixels is processed. The amount of eggs is counted from each DFL by visual inspection to compare with count obtained from image processing algorithms experimented. Image processing algorithms and GUI implemented to display the results to user in MATLAB.

The explored algorithm evaluated is based on color segmentation and mathematical morphology. Figure 1 shows the sample image of one DFL which actually consist of 585 eggs. A color digital image of size 1,600 × 1,200 is converted to gray image as RGB color models are not well suited for describing the colors it terms that are not well suited for human interpretation[10].

This conversion of RGB image to grayscale is carried out by eliminating the hue and saturation information while retaining the luminance. The applied transformation is as per equation (1)

$$\text{Grayscale} = (0.2989 \times \text{R}) + (0.5870 \times \text{G}) + (0.1140 \times \text{B}) \tag{1}$$

where R, G, and B are the values of the red, green, and blue components.

The image shown in Fig. 2 has a uniform background but is now a bit too bright. The contrast of gray image is enhanced by mapping the values in intensity image to new values such that 1 % of data is saturated at low and high intensities of original image. This increases the contrast as shown in Fig. 3 .

Figure 3 is binarized using Otsu's method which uses a global threshold to convert the intensity image to binary image[10]. Otsu's method is used to find out

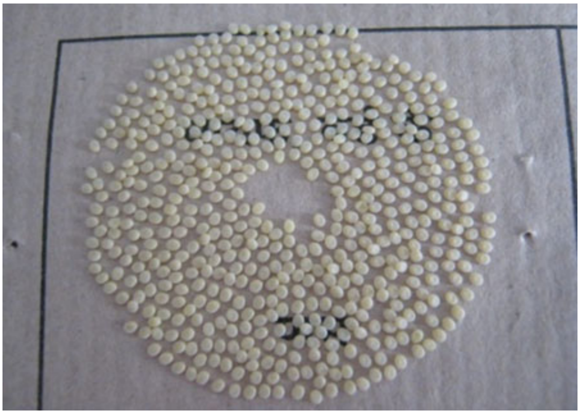

Fig. 1 Sample of DFL

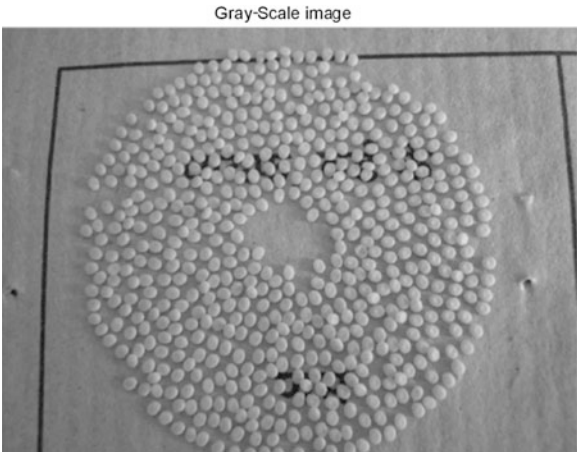

Fig. 2 Gray scale image

the global threshold level to minimize the intraclass variance of thresholded black and white pixels. The applied transformation is as per equation (2)

$$\begin{aligned} S(x,y) &= 1\ldots\text{if } r(x,y) > \text{ threshold} \\ &= 0\ldots\text{if } r(x,y) < \text{ threshold} \end{aligned} \tag{2}$$

where $r(x, y)$ represents the pixels of original image and $S(x, y)$ represents the pixels of thresholded image. Figure 4 shows the result of thresholding. In this image, the background illumination is brighter in the top right corner of the image than at the bottom left corner. This is the effect of nonuniform illumination. Hence, this gray image shown in Fig. 3 is filtered using TopHat Filtering. An important use of top-hat transformation is in correcting the effects of nonuniform illumination. It performs morphological opening on grayscale or binary image with structuring element. Morphological opening operation is erosion followed by dilation using same structuring element for both operation.

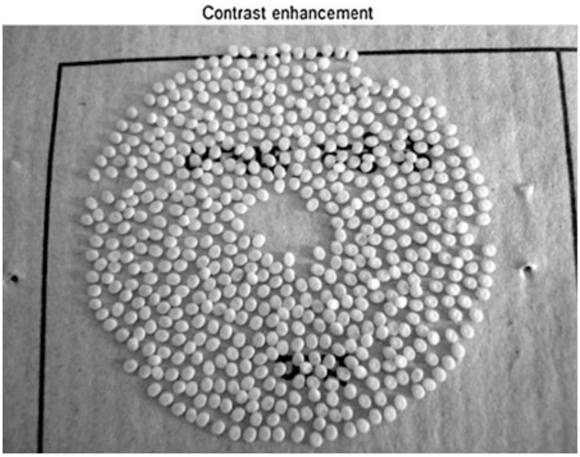

Fig. 3 Contrast enhancement

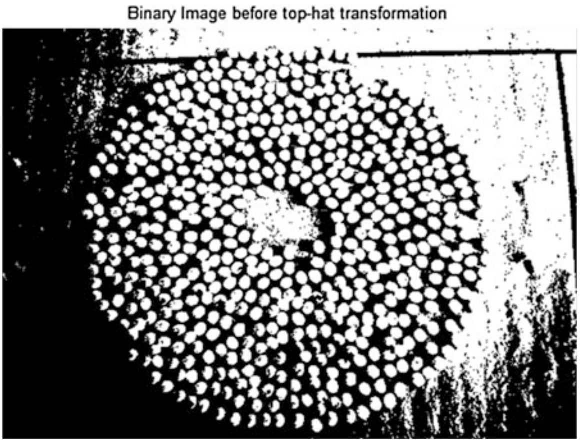

Fig. 4 Thresholding before applying top-hat filtering

A morphological opening operation is used to estimate the background illumination.

$$\text{TopHat filtering} = \text{Image} - \text{Opening of image}$$

The opening operation has the effect of removing objects that cannot completely contain the structuring element. After applying top-hat filtering, we get the better results for thresholding as shown in Fig. 5.

Small areas can be deleted as it could not contain an egg. This experiment has defined that every area with less than 100 pixels should be deleted. Figure 6 shows the result of removing background noise due to which unwanted small objects from background are removed. Figure 6 shows there are some eggs which overlap with one another. To separate them, erosion is applied which reduces the size of each egg. Erosion is performed with the disk shaped structuring element so that

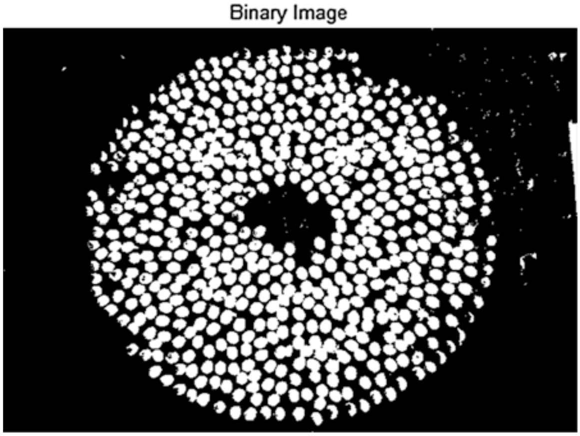

Fig. 5 Thresholding after applying top-hat filtering

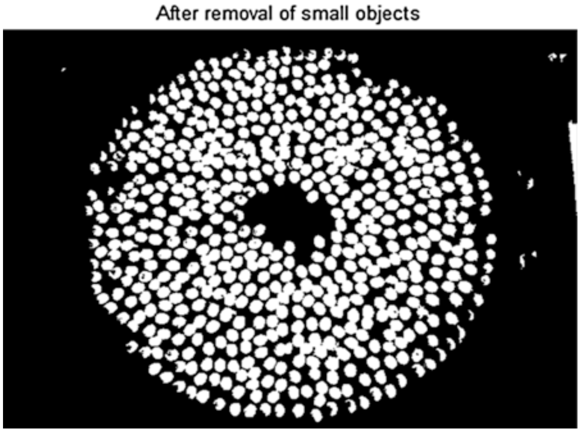

Fig. 6 After removal of small objects

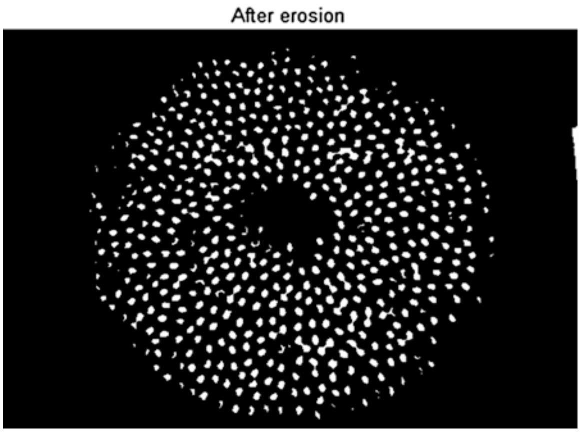

Fig. 7 After erosion

Table 1 Counting results using proposed method

Image	Correct amount of eggs	Estimated amount of eggs by proposed algorithm
1	585	582
2	622	627
3	541	540
4	695	684
5	525	532
6	518	536

some of the connected regions get eliminated. Figure 7 shows the result of erosion due to which some of connected eggs are removed.

With the binary image, a connected components algorithm is applied to label the connected regions of the image. This algorithm puts a different label at each connected white area of the image. With this labeling, it is possible to evaluate each connected area. This gives the number of connected objects found in image which represents the number of eggs in image.

Discussion and Result

Table 1 presents the results of the explored algorithm applied to another five sample images with different count. The image labeled as ‘1’ in Table 1 is the image previously presented in Fig. 1 with 585 eggs.

From the results given in Table 1, the overall accuracy for method is 93.31 %. These algorithms were tested for 19 different images.

Conclusion and Future Scope

The algorithm evaluated is simple and efficient. It is sensitive to the nonuniform illumination. If illuminating pattern varies significantly, this method does not show the accurate count of eggs. Using image processing techniques, we can find the number of eggs present in an image. This reduces the time of counting significantly. Accuracy of results depends upon size of objects, whether or not any object are touching (in which case they might be labeled as one object), accuracy of approximated background and the connectivity selected.

This work can be extended to count the number of eggs from sheet containing many DFLs. A dedicated hardware can be implemented to count the eggs using programmable logic devices such as FPGA and CPLD which can give rise to higher speed of computation. Web-based counting mechanism can also be implemented by using proposed method.

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