J. Crop Prot. *2016, 5 (1): 59-73*
doi: 10.18869/modares.jcp.5.1.59

Research Article

A novel automated image analysis method for counting the population of whiteflies on leaves of crops

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Abstract: Counting the population of insect pests is a key task for planning a successful integrated pest management program. Most image processing and machine vision techniques in the literature are very site-specific and cannot be easily re-usable because their performances are highly related to their ground truth data. In this article a new unsupervised image processing method is proposed which is general and easy to use for non-experts. In this method firstly a hypothesis framework is defined to distinguish pests from other particles in a captured image after texture, color and shape analyses. Then, the decision about each hypothesis is made by estimating a distribution function for sizes of particles which are presented in the image. Performance of the proposed method is evaluated on real captured images that belong to plants in green houses and farms with low and high densities of whiteflies. The obtained results show the greater ability of the proposed method in counting whiteflies on crop leaves compared to adaptive thresholding and K-means algorithms. Furthermore it is shown that better counting of the pest by proposed algorithm not only doesn't lead to extracting more false objects but also it decreases the rate of false detections compared to the results of the alternative algorithms.

Keywords: pest population monitoring, image processing, whiteflies, size distribution

Introduction

Plants play a vital role in human life on earth maintaining oxygen, food, medicine and more. Pest population monitoring is one of the most important tasks in monitoring growth procedure of many plants in agriculture (Afshari *et al*., 2009; Kapur *et al*., 1985; Mundada and Gohokar, 2013). Integrated Pest Management (IPM) is an effective and environmentally sensitive approach to pest management which promotes methods to fight pests while minimizing the use of pesticides. Pesticides are very harmful to crops, soil, air, water resources and animals which come in contact with pesticides. The IPM approach is promising and requires frequent and precise observations of plants under natural growing conditions (Baumgärtner and Gessler, 2002). Counting whiteflies on leaves helps in making decisions as to what would be the proper method to prevent spread of pests and find the optimum amount of pesticides. After the control process, counting the number of pests shows the effectiveness of the control method.

The main problem in such monitoring is to count small size pests in large dimensions of greenhouses and farms. For many years pests have been studied using visual observations, which have been done frequently by experts in farms and greenhouses (Hanafi, 2003). Although

Handling Editor: Yaghoub Fathipour

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Received: 01 February 2015, Accepted: 18 September 2015
Published online: 11 December 2015

this method could provide precise information about pests, it has three main limitations. Firstly it is time consuming and secondly it depends on observer's skills and is vulnerable to human errors and thirdly it is not possible to perform a continuous time-control on considerable number of leaves in large and daily growing farms and greenhouses. In order to solve these problems, computer vision systems have been proposed as a high-technology solution for pest monitoring and management under natural conditions. These systems at first utilize a combination of controllable cameras which provide images. In the next step, several image processing algorithms are applied in order to detect, classify, count and track harmful pests (Bechar *et al*., 2010; Martin *et al*., 2008; Mundada and Gohokar, 2013).

Whiteflies are considered as one of the most harmful pests for several agricultural products. There are two approaches in the literature of whitefly automatic counting; one is focused on sticky traps to detect insects on them (Cho *et al*., 2007; Kumar *et al*., 2010; Xia *et al*., 2012; Martin *et al*., 2008) and the other tends to detect whiteflies on leaves of plants. In this paper the second approach has been chosen, because in the first one pest must be able to fly to reach sticky traps and at this stage of insects' development, the damage has already been done to crops. Several methodologies have been proposed to find solutions to detect and count whiteflies on leaves by means of image processing and machine learning techniques. Some of them have utilized global and local thresholding algorithms (Bodhe and Mukherji, 2013; Huddar *et al*., 2012). Unfortunately these methods are mainly unable to detect whiteflies accurately due to presence of some bright background objects such as veins or dews. Also for smooth textured leaves, some parts of leaves may be much brighter in the image because of the reflection of the light to the camera lens. These parts may have close intensity distributions to whiteflies. Therefore, the resulting histograms would not be the desired bimodal and thus some background particles may be detected as whiteflies in images.

Another group of methods utilize color as a discriminative feature between pests and background (Cho *et al*., 2007). They specify some color ranges for whiteflies and some ranges for leaves. These methods are not only dependent on ground truth data but also they are not flexible to the change of light. In addition, some parts of a leaf may be in shadow and other parts may be in light and the difference between color specifications of these parts would degrade segmentation results.

One of the well-known algorithms which have achieved good performance in segmenting whiteflies is the watershed segmentation method (Boissard *et al*., 2008). In each image there might be some components of the leaf such as bright veins, and particles such as eggs of the pests and dews, that may cause many local minima and so lead to over segmentation of the image using this method. With the aid of the size of the whiteflies in the image, a series of morphological operations can be applied with the intent of creating approximate foreground and background markers to remove spurious minima and overcome the problem of over segmentation, therefore the performance of this method is highly related to the knowledge of the size of whiteflies on an image. Consequently this method is ground truth dependent.

The applications of many proposed methods in the literature are very specific and their performances are highly related to their ground truth templates. Thus, they cannot be easily re-usable for other situations. On the other hand, whiteflies have a host range of more than 250 plants which may grow in different site specifications. So, it is important to find a method which is more general and can be applied for several situations. To this end, the objective of this paper is to propose a general detection system which is not site-specific. A very significant parameter for the goal of finding a general detecting method without knowing ground truth data is the size of pests in an image. In this article a novel method for counting whiteflies on leaves has been proposed in which the size of whiteflies in an image is found and then by considering this information, the optimum texture, color and shape analysis steps are applied in order to detect and count number of whiteflies in images that are captured from crops leaves.

Materials and Methods

Materials

The database used for the development of the algorithm consists of 200 images which have been divided in two groups; in the first group there are images in which the densities of whiteflies are low and therefore they are almost well separated. The second group consists of images with high density of whiteflies in which near distances between pests may degrade the performance of detection algorithms. Specifications of the database are shown in table 1.

The proposed algorithm and two rival algorithms were implemented using Matlab 2009.

Proposed method

The proposed algorithm has been designed according to three basic properties of whiteflies in such images; 1) whiteflies seem to be brighter objects than other parts of an image. 2) The size of whiteflies in each image is the same. 3) The most non-homogeneous part of these images are the parts that the insects exist and the texture of an image in these areas changes greatly.

To better illustrate the steps of the proposed algorithm, the flowchart of the proposed algorithm is presented in Figure 1 and the steps of the algorithm are depicted by a sample image response to each step:

In gray-scale images, contrast between whiteflies and leaves are higher, therefore at first the RGB image is converted to the gray scale intensity image. The gray-scale value for each pixel is calculated as follows:

$$I = 0.2989R + 0.5870G + 0.1140B \qquad (1)$$

Figures 2 (a) and (b) show RGB and gray scale representations of the sample image respectively.

Shape analysis

In mathematical morphology, granulometry is an approach to determine size distributions of objects in an image without explicitly detecting each object (Gonzalez and Woods, 2002; Vincent, 1994). The method consists of applying morphological openings with structuring elements (SE) of increasing size, for each opening, the sum of the pixel values in the opening is computed. SE is an element that seems like the target objects. This procedure yields a 1-D array of such numbers, with each element in the array being equal to the sum of the pixels in the opening for the size SE corresponding to that location in the array. To emphasize changes between successive openings, the difference between adjacent elements of the array is computed. Maximum of the difference diagram indicates large quantity of the corresponding size. Because the gray scale intensities of pests in images are the highest, this size indicates the size of the whiteflies. The width of the pests is twice this radius. The difference diagram for the sample image is shown in figure 3. The width of the pests in this image is 2 × 9 i.e. 18.

Gray scale intensity analysis

In the first step, the RGB images have been converted to gray scale intensity images because intensity images are enough for the proposed method. After finding the size of whiteflies by using a structuring element of this size, the morphological tophat transform (Gonzalez and Woods, 2002; Vincent, 1994) is applied which is an operation that brightens the elements of that size in an image. Then the median filter is applied to remove noise from the image. Figure 4 (a) shows the resultant image. Applying tophat transformation in the previous step makes the gray scale image histogram to be bimodal. The minimum thresholding is suitable for segmenting this kind of images (Gonzalez and Woods, 2002; Vincent, 1994). If the histogram is clearly bimodal, it is easy to find the minimum value between two maximums which is the threshold value. But if it contains multiple minima an algorithm for smoothing the histogram is needed in order to construct the histogram which contains only one minimum. Figure 4, (b) and (c) show the histogram of the tophat transformed image and its smoothed version respectively. The black and white image after applying the threshold which has been 213 is depicted in figure 4 (d).

[DOR: 20.1001.1.22519041.2016.5.1.15.4]

Table 1 Specifications of test scenarios.

Min size of images (pixels)	Max size of images (pixels)	Min length of insects (pixels)	Max length of insects (pixels)	Number of captured images	Min-Max population of insects per image (First Scenario)	Min-Max population of insects per image (Second Scenario)
72*49	1641*1915	18	243	200 (100 for each scenario)	1-30	30-300

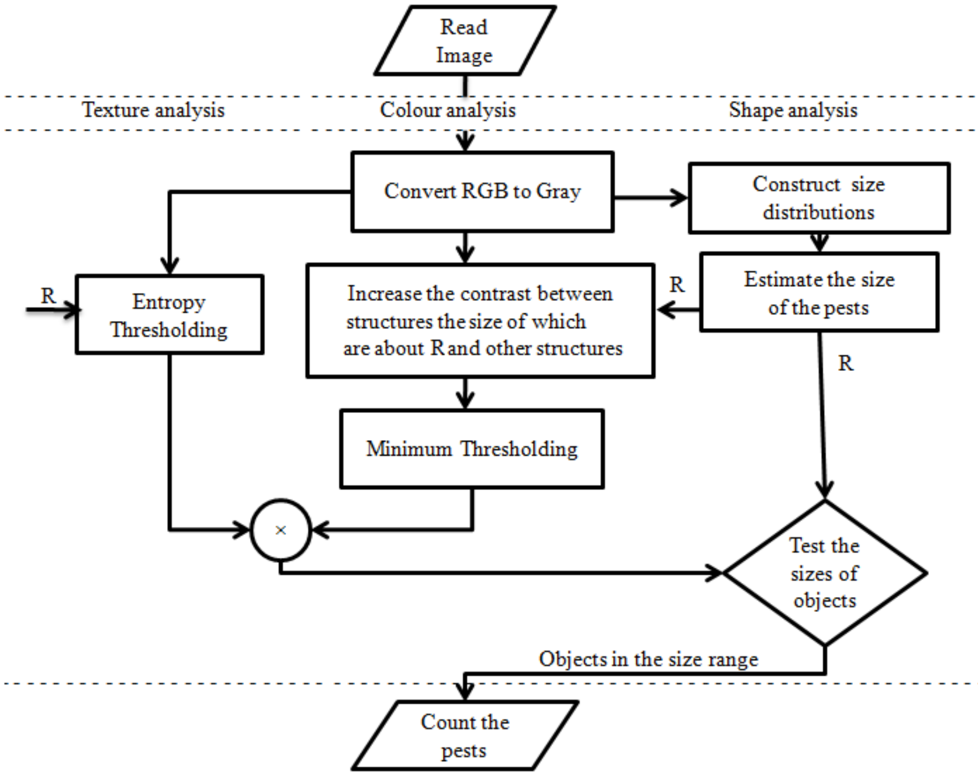

Figure 1 Flowchart of the proposed automated counting algorithm.

Texture analysis

In an image the areas in which the pests exist, the texture of the image greatly changes. Therefore the entropy property was chosen to assess the textures in the images. For this purpose the partial entropy E_{2R-1} is calculated for all gray levels $q_i = [0\,255]$ where each output pixel contains the entropy value of the (2R-1) by (2R-1) neighborhood around the corresponding pixel (Gonzalez and Woods, 2002; Vincent, 1994) as follows:

$$E_{2R-1} = \sum_{i=1}^{(2R-1)^2} q_i \log q_i \tag{2}$$

As can be seen in figure 5 (a), high entropy values indicate non-homogenous parts and low entropy values indicate homogenous parts. Threshold η_E is calculated using minimum thresholding algorithm described in section 2.2.2 and upper values are chosen as candidates for whiteflies. Figure 5 (b) shows the extracted candidates after texture analysis step. This step not only extracts whiteflies on leaves but also helps to separate adjacent whiteflies. If for example two whiteflies were in contact with each other, the (2R-1) by (2R-1) neighborhood around the contacting border is placed among the region of pests and this region is homogeneous. Therefore entropy values for connected boundaries are low.

Finally as has been depicted in figure 6, the intersection of texture and Intensity analysis steps are tested and the detected particles which sizes are about the estimated size are counted as whiteflies.

Figure 2 (a) RGB image, (b) gray scale image of a sample image used for depicting the proposed automated counting algorithm.

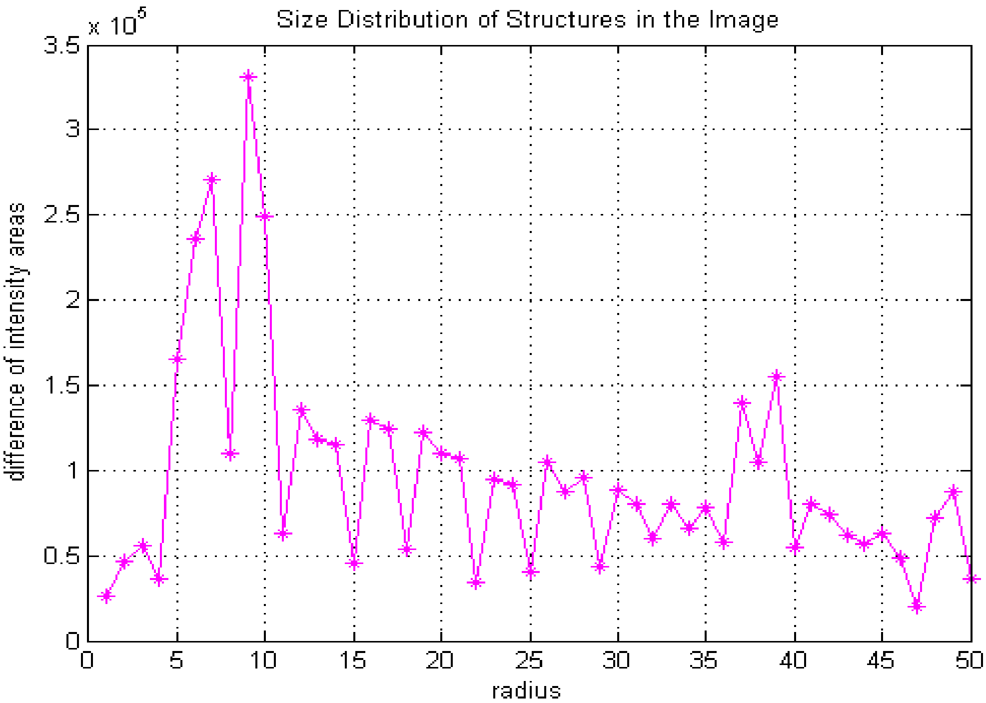

Figure 3 The difference diagram for the sample image used for depicting the proposed automated counting algorithm, the abscissa is the radius of structuring elements and the ordinate is the calculated difference between intensities of the opened images with structuring elements of successive sizes, the width of the pests is twice the radius of the structuring element which relates to the maximum difference.

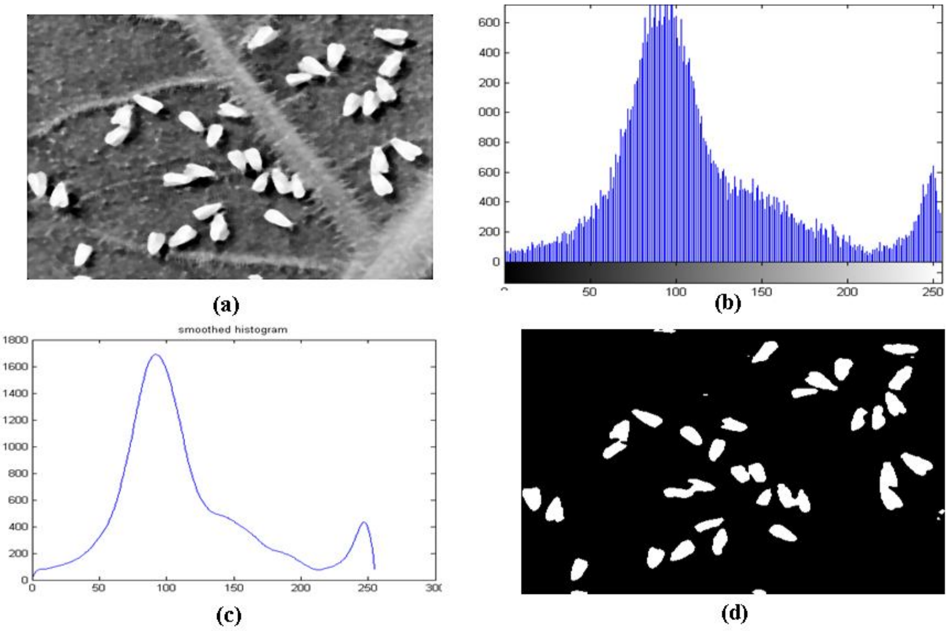

Figure 4 Intensity analysis for the sample image used for depicting the proposed automated counting algorithm: (a) Tophat transform, (b) histogram of tophat transform, (c) smoothed histogram that contains only one local minimum, (d) black and white result from minimum threshoding.

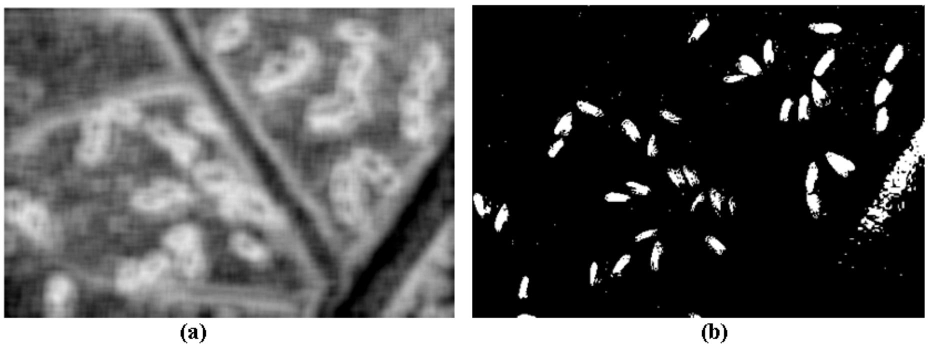

Figure 5 Texture analysis for the sample image used for depicting the proposed automated counting algorithm: (a) Local entropy highlight the non-homogeneous areas and darken the homogeneous ones specially the middle border of adjacent whiteflies is darkened in order to separate them, (b) black and white image after thresholding.

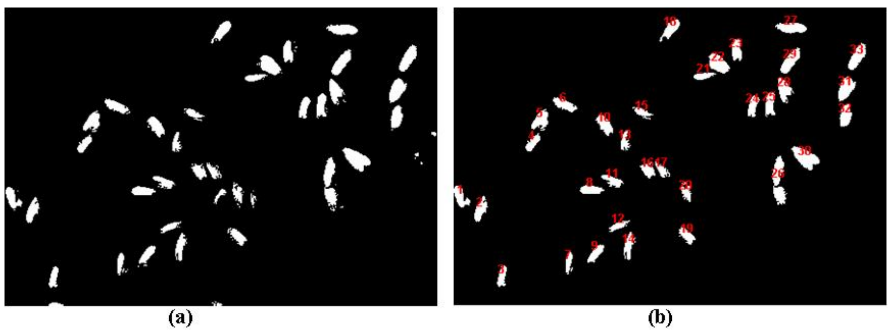

Figure 6 (a) The intersection of texture and Intensity analysis for the sample image used for depicting the proposed automated counting algorithm, (b) the result from size testing step and counting pests.

Evaluation method

In the literature there are two rivals for the proposed method. The first alternative algorithm is K-Means Segmentation algorithm which has been applied in (Fina *et al*., 2013). K-Means algorithm is an unsupervised clustering algorithm that classifies input data points into multiple classes based on their inherent distance from each other (Kanungo *et al*., 2002). The second one is Adaptive Thresholding algorithm which has been used in (Woon, 2004). Adaptive thresholding algorithm classifies image pixels by considering spatial variations in illumination (Chan *et al*., 1998). K-Means and Adaptive thresholding algorithms are called (KMS) and (ATA) respectively for brevity in the rest of the paper. They have been chosen because they are unsupervised methods and do not require information about databases. Also among other detection methods in the literature, these two methods are capable of segmenting whiteflies in our general database.

The results of the proposed method and two rival algorithms were compared with each other using F1 score and False Discovery Rate (F1 and FDR respectively). F1 score is a measure of a test's accuracy and defined as:

$$F1 = \frac{2TP}{2TP + FP + FN} \tag{3}$$

where TP, FP and FN represent correctly identified pests (i.e. True Positives), incorrectly identified pests (i.e. False Positives) and incorrectly rejected pests (i.e. False Negatives) respectively. False Discovery Rate (FDR) implies the ratio of the number of errors to the counted number in each algorithm and is defined as:

$$FDR = \frac{FP}{FP + TP} \tag{4}$$

Test images were processed manually to obtain a reference to evaluate performances of the algorithms. The total number of whiteflies in an image is denoted as "P", the number of detected particles using each algorithm is denoted as "no" and "*TN*" (i.e. True Negatives) is the number of whiteflies which were not detected. The required parameters for constructing F1 score and FDR for each result are calculated as below:

Since the proposed algorithm extracted minimum number of *TN*, it was manually counted and regarding it P is counted as:

$$P = no + TN \tag{5}$$

For each algorithm *FP* was counted manually and *TP* and *FN* were counted as below:

$$TP = no\text{-}FP \tag{6}$$

$$FN = P\text{-}TP \tag{7}$$

Results

For the reason of clarity and to avoid crowded figures, the labels of the whiteflies for the results of the algorithms were not shown in the figures 9 and 10.

Figure 7 shows one of the obtained results belonging to the case that brightness intensities of the veins and other particles of the leaf are not close to the intensities of whiteflies. Therefore none of the algorithms extracted false objects. However it is clear that the proposed method is the best among two other methods in separating joint whiteflies.

Figure 8 demonstrates the results for an image in which the gray scale intensities of veins are about the intensities of whiteflies. As it can be seen, the proposed algorithm successfully has omitted this kind of background particles while the other algorithms have had problems to distinguish between these particles and the insects. The proposed method has not extracted any false particles, while using KMS and ATA algorithms 11 and 9 background particles have been detected as whiteflies wrongly.

In figure 9 one of the rare test images in which the result of the proposed algorithm contained some false detected particles is presented. The false particles have been bolded in the results by yellow boxes. The results show that applying the proposed method among 29 pests in the original image, 26 whiteflies have been extracted correctly and 4 background particles were detected as whiteflies incorrectly. Using ATA and KMS 22 and 19 whiteflies have been detected correctly respectively. Also 7 and 15 background particles were extracted wrongly.

The reason of extracting some part of veins as whiteflies is that eggs of whiteflies make the structure of the veins segregated and the size of some segregated parts are about the size of the whiteflies, and then the proposed algorithm has not been able to diagnose them from whiteflies. As it can be seen from that figure the performances of the two other algorithms are much worse than the proposed algorithm.

Figure 10 demonstrates one of the obtained results from processing of the captured images containing high population of pests. The proposed method has extracted 145 whiteflies from among 161 existing whiteflies in the image without extracting any false object. By using ATA method 105 correct pests and 50 false objects have been extracted. Here the poor performance of KMS method is notable which has extracted 67 correct pests and 151 false objects. The ability of the proposed method to separate and count joint whiteflies is because of the texture analysis step. The middle border of adjacent whiteflies in this step comes apart from whiteflies.

In accordance with the standard approach in pest detection literature (5), F1 score and FDR values have been depicted in four separate plots versus the ordered test samples as have been shown in figures 11-14; also the average values of F1 score and FDR in the first and second scenarios have been listed in Table 2.

Table 2 Mean value of the F1score and FDR for the results of the scenarios.

Algorithms	The proposed method (%)	ATA[1] (%)	K-Means (KMS) (%)
First Scenario (Low Density)			
Average of F1 scores (accuracy)	85.0	67	55
Average of FDRs (inaccuracy)	0.7	20	21
Second Scenario (High Density)			
Average of F1 scores (accuracy)	74.0	30	25
Average of FDRs (inaccuracy)	0.6	49	54

1. Adaptive Thresholding Algorithm.

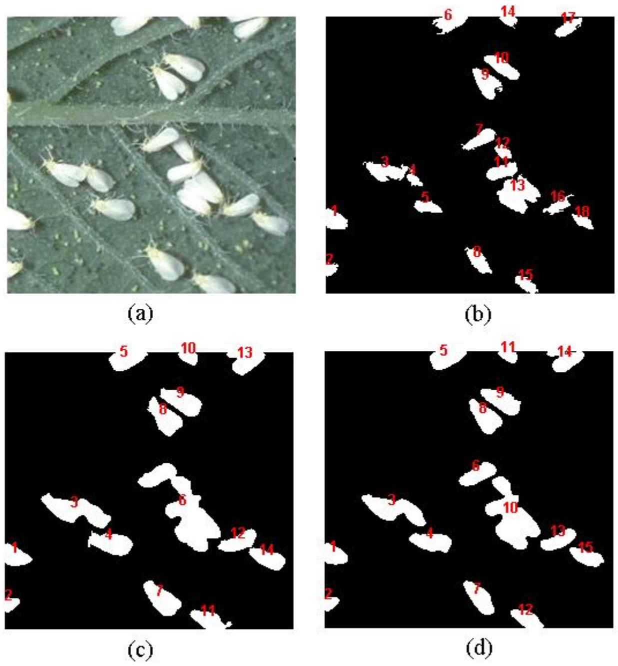

Figure 7 One of the sample results from the first scenario. (a) The sample image. The resultant extracted insects using (b) the proposed algorithm (c) KMS algorithm and (d) ATA algorithm.

[DOR: 20.1001.1.22519041.2016.5.1.15.4]

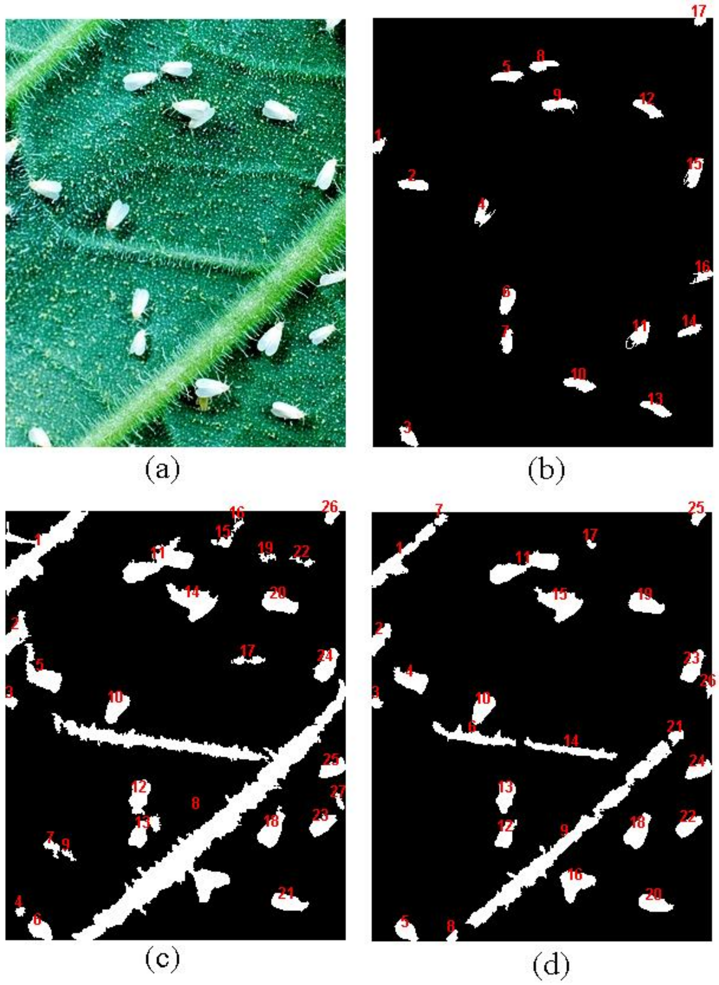

Figure 8 One of the results from the first scenario, (a) The sample image. Extracted insects using (b) the proposed algorithm (c) KMS algorithm and (d) ATA algorithm.

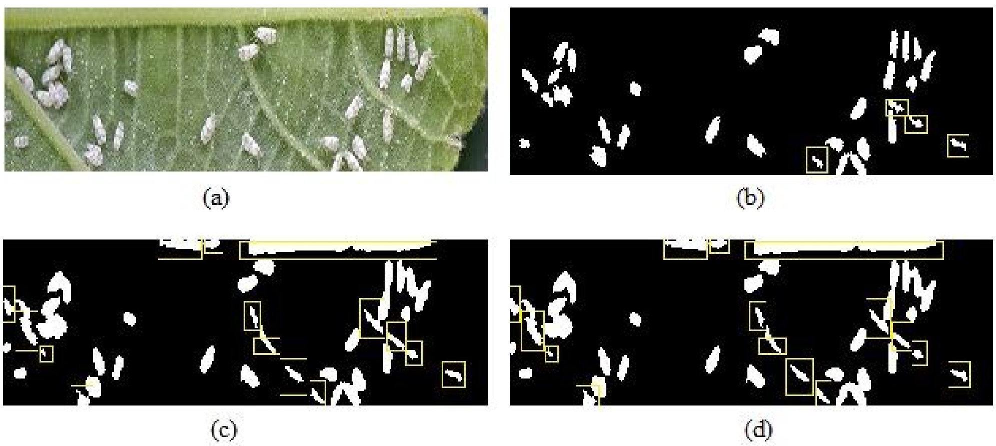

Figure 9 One of the results in which the proposed algorithm extracted some false objects. (a) The captured image. Extracted insects using (b) the proposed algorithm (c) KMS and (d) ATA algorithm.

[DOR: 20.1001.1.22519041.2016.5.1.15.4]

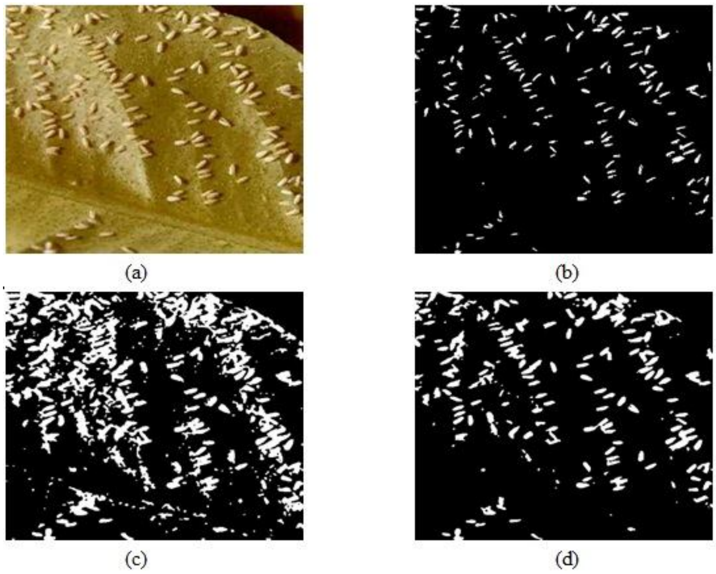

Figure 10 One of the results from the second scenario with very high population of insects. (a) The captured image. Extracted insects using (b) the proposed algorithm (c) KMS algorithm and (d) ATA algorithm.

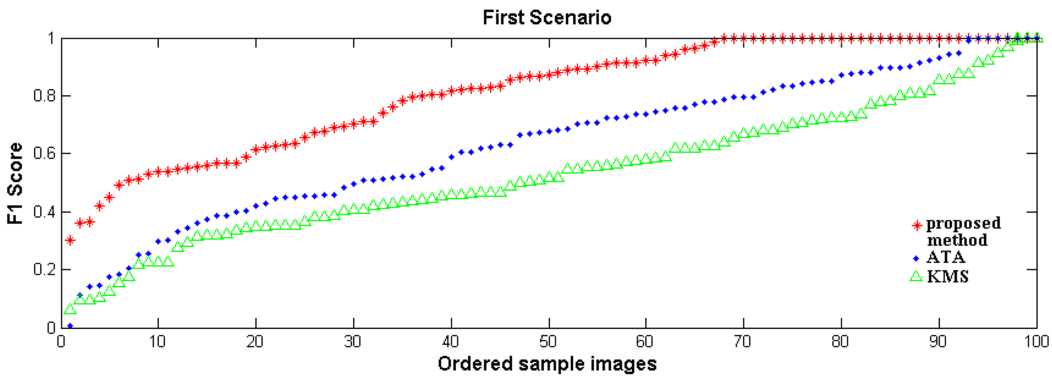

Figure 11 F1 score parameter for proposed, ATA and KMS algorithms in first scenario. (F1 score is a measure of accuracy of the algorithms).

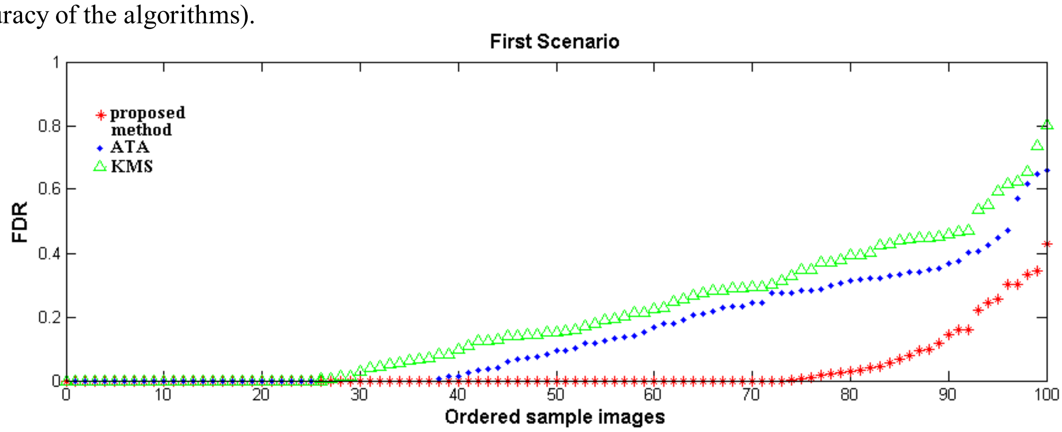

Figure 12 FDR parameter for proposed, ATA and KMS algorithms in first scenario. (FDR is a measure of false detections or inaccuracy).

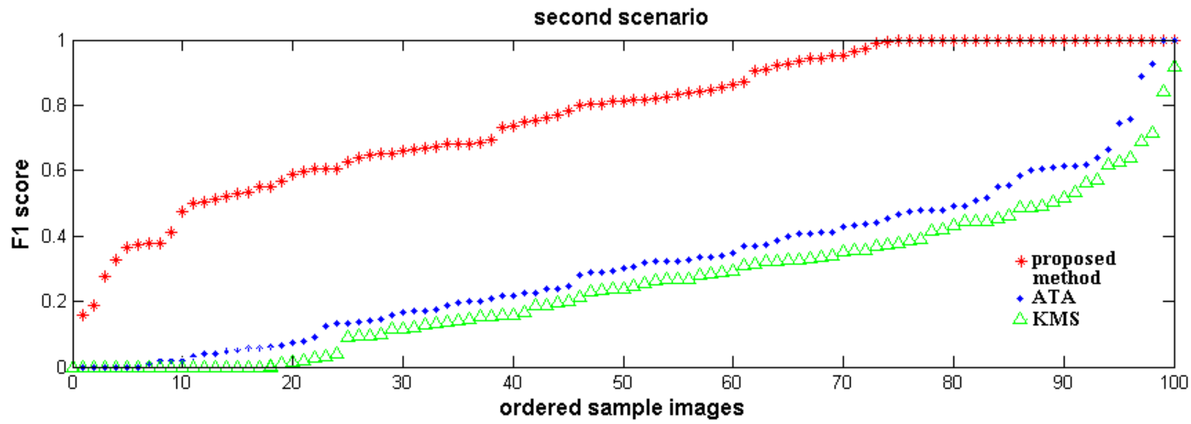

Figure 13 F1 score parameter for proposed, ATA and KMS algorithms in the second scenario. (F1 score is a measure of accuracy of the algorithms).

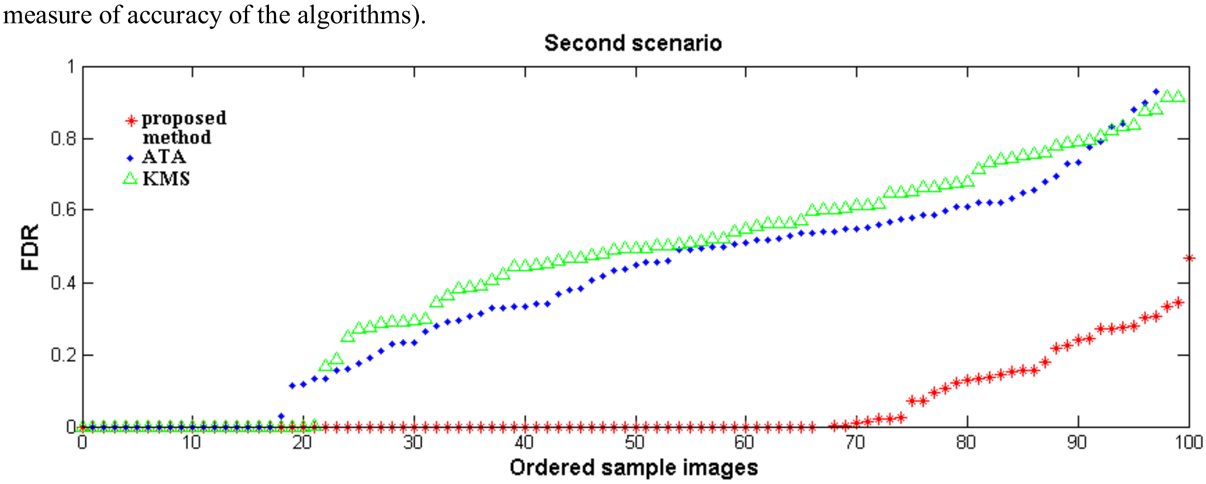

Figure 14 FDR parameter for proposed, ATA and KMS algorithms in the second scenario. (FDR is a measure of false detections or inaccuracy).

Based on the table 2, in the first scenario, the F1 values of the proposed method have been 18% and 30% better than ATA and KMS methods respectively. By comparing the results of the first and second scenarios in table 2, it is observed that in parallel with increasing the population of pests in the second scenario, separating adjacent whiteflies became more difficult. This led to decreases in F1 values of the proposed method, ATA and KMS methods by as much as 11%, 37% and 30% compared to the first scenario respectively. Despite these decrements, the superiority of the proposed method compared to alternative methods has been more pronounced in the second scenario. In this case the mean F1 of proposed method has been 44% and 49% better than ATA and KMS results respectively.

Investigation of FDR values for examined algorithms, demonstrates the superiority of the proposed method compared to its alternatives. Based on table 2, the average FDR which is obtained using the proposed algorithm has been 19.3% and 20.3% lower than ATA and KMS methods in the first scenario. In the second scenario this parameter has been 48.4% and 53.4% lower than ATA and KMS respectively.

Discussion

The proposed method has been designed in order to find a general method, for the problem of unsupervised automated counting of whiteflies on crops' leaves by means of image processing techniques. the major information required for this aim is the size of whiteflies on each image. The proposed method presents a novel approach for estimating this information automatically for each image. Three main steps, namely intensity analysis, texture analysis and shape analysis have been optimized utilizing the size information in order to enhance the performance of the proposed method in comparison with other unsupervised methods. There are two main difficulties for counting this pest on leaves. One is a near distance between whiteflies in images with high densities of whiteflies which makes problems for counting them individually. The other is the existence of bright parts on leaves such as bright veins, dews, dust and whitefly eggs which makes the automated algorithms be confused and detect false objects. In the proposed method, the texture analysis step utilizing size information successfully separate joint whiteflies by means of local entropy thresholding. The results of figure 10 and the superiority of the algorithm in the second scenario from table 2 are evidences of this ability of the proposed algorithm. On the other hand, the combination of the three steps along with size information enables the proposed algorithm to get rid of detecting false particles as can be deduced from figure 8 and FDR results of table 2. The obtained results demonstrate considerable superiority of the proposed method in comparison with its alternatives as can be seen from figures 7-14 and table 2. One of the reasons for this superiority is utilizing the size information that is obtained in the first step of the proposed method. This information enables the algorithm to optimize thresholding results. In contrary, two rival methods find threshold values without considering size information. The other reason for this superiority is that the proposed algorithm combines three main characteristics of this kind of databases, namely intensity, texture and shape together which makes it highly robust. But, the two rivals only consider intensity characteristics of the image. Thus, the performance of the new method is much better than its alternatives.

Conclusion

In this paper a new method for automated counting of whiteflies on crops' leaves has been introduced. Estimation of the size of pests and paying attention to the shape, texture and intensity characteristics of whiteflies and leaves enables the proposed algorithm to be flexible to many various situations which makes it unsupervised and independent of ground truth data. The obtained results demonstrate considerable superiority of the proposed method in comparison with its alternatives. The accuracy of the results using the proposed algorithm was much better than the others and especially in the second scenario in which the densities of whiteflies on leaves were much higher this superiority is considerable. The results showed the power of the proposed algorithm regarding the prevention of detecting false particles and noise. Consequently the proposed method can be used as a suitable automatic unsupervised method for counting whiteflies in natural conditions of greenhouses and farms without the need for ground truth data.

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Appendix

This appendix is devoted to make the paper easier to understand for readers interested in some basic image processing techniques which have been utilized in our paper.

Suppose I be a sample gray scale image. Each pixel of the image is indicated as:

$$I_{m,n} = I(m,n) \text{ and } 1 \leq m \leq M,\ 1 \leq n \leq N. \qquad \text{(A.1)}$$

In which, $I_{m,n}$ is the gray scale intensity of a pixel which is located in the row and column equal with m and n respectively. Furthermore, M and N are the length and width of the image.

[DOR: 20.1001.1.22519041.2016.5.1.15.4]

Gray Scale Opening

The value of opened gray scale image *I* by a structuring element *S*, in the row and column equal with *m* and *n* is defined as follows:

$$O\left(I,S\right)_{m,n} = ((I\ !\ S)_{m,n} \oplus S)_{m,n}. \qquad \text{(A.2)}$$

In which, Θ and ⊕ are the erosion and dilation operators respectively. They were defined as follows:

$$\left(I\ !\ S\right)_{m,n} = \min\left(I_{i,j}\right)\Big|_{i,j\in S\left(I\left(m,n\right)\right)} \qquad \text{(A.3)}$$

$$\left(I \oplus S\right)_{m,n} = \max\left(I_{i,j}\right)\Big|_{i,j\in S\left(I\left(m,n\right)\right)} \qquad \text{(A.4)}$$

in which $I_{i,j}$ are neighboring pixels allocated in the structuring element area which its determiner point is coincident with the pixel $I_{m,n}$.

Top-hat Transform

Top-hat tranform is defined as the difference between the input image and its opening by some structuring element:

$$T\ \left(I,S\right)\ = I - O\left(I,S\right). \qquad \text{(A.5)}$$

Gray Scale Histogram

The gray-scale histogram of an image represents the distribution of the pixels in the image over the gray-level scale. To construct a gray scale histogram, the number of pixels which have the same intensities in the range of 0 to 255 are counted and displayed on a graph which its abscissa is intensity and its ordinate is the number of corresponding pixels. The histogram of an image *I* described as follows:

$$H_{(I)}\left(z\right) = \sum_{i=1}^{255} h_i\,\delta\left(z - i\right) \qquad \text{(A.6)}$$

In which h_i denotes the number of pixels that have the intensity i and δ is the discrete unit impulse function.

The algorithm for smoothing the histogram

One of the useful smoothing algorithms is the "rectangular sliding-average smooth." This method replaces each point in the histogram with the average of "m" adjacent points, where "m" is a positive integer called the "smooth width." In the proposed algorithm this smoothing algorithm has been applied in a way that its smoothing width was equal to 3.

$$h_i\,' = \frac{h_{i-1} + h_i + h_{i+1}}{3} \qquad \text{(A.7)}$$

In order to find the minimum thresholing value, this algorithm should be iterated until only one local minimum remains in the histogram.

روشی نوین بر مبنای پردازش رایانه‌ای تصاویر جهت شمارش خودکار جمعیت آفت سفیدبالک روی برگ‌های محصولات

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دریافت: ۱۲ بهمن ۱۳۹۳؛ پذیرش: ۲۷ شهریور ۱۳۹۴

چکیده: تخمین جمعیت آفات گیاهی یکی از فرایندهای مهم و اساسی برای برنامه‌ریزی موفق جهت مدیریت آفات می‌باشد. بیش‌تر روش‌های پیشین مبتنی بر پردازش تصویر و بینایی ماشین که در این زمینه ارائه شده طوری طراحی شده‌اند که فقط برای یک فضای خاص قابل اعمال هستند و برای محیط‌های دیگر با شرایط مختلف جوابگو نیستند و عملکرد آنها وابسته به اطلاعات مربوط به محل مورد بررسی می‌باشد. در این مطالعه روشی نوین بر مبنای پردازش تصویر توسط کامپیوتر برای مشخص کردن و شمارش آفت مگس سفید روی برگ‌های گیاهان آفت‌زده ارائه شده است که عمومی می‌باشد و نیازی به اطلاعات نمونه‌ها ندارد و در شرایط و مکان‌های مختلف قابل استفاده می‌باشد. در این روش با استفاده از سه مرحله، بررسی شکل، بافت و رنگ تصویر و با استفاده از تخمین خودکار اندازه آفت در تصاویر مورد بررسی، آفات سفیدبالک از سایر قسمت‌های برگ محصول متمایز شده و شمارش می‌گردد. عملکرد روش ارائه شده روی عکس‌هایی از برگ‌های گیاهان مختلف با چگالی آفات کم و زیاد در گلخانه‌ها و مزارع امتحان شده است. نتایج به‌دست آمده نشان می‌دهد که عملکرد این روش در شمارش آفت سفیدبالک از روش‌های ارائه شده قبلی بهتر بوده و این بهبود در شمارش آفات نه‌تنها موجب افزایش احتمال شمارش اجزای نادرست نمی‌شود بلکه درصد آشکارسازی‌های اشتباه را نیز پایین آورده است.

واژگان کلیدی: نظارت بر جمعیت آفات، پردازش رایانه ای تصاویر، آفت سفیدبالک، توزیع اندازه

[DOR: 20.1001.1.22519041.2016.5.1.15.4]