Robust Insect Classification Applied to Real Time Greenhouse Infestation Monitoring

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Abstract

Our purpose is to develop a classification system for the automatic detection of harmful insects in greenhouse plants. This paper deals with evaluation of three feature extraction techniques for classification of insects. Feature extraction methods used are Gabor Filters, Pyramidal Histogram of Gradients and color data. The aim of the classification machine apart from achieving high degree of accuracy is to reduce number of false negatives. Different feature extraction methods is evaluated based on total accuracy, number of false positives & false negatives, Precision Recall & ROC curves and computation time.

1. Introduction

Classically pest monitoring is performed manually and relies heavily on the knowledge and availability of human expert for routinely screening every greenhouse crop to predict prominent pest attacks at the early stage, thereby manage to optimize the fighting operations that fall. The idea developed here is to equip a greenhouse crop with a network of video cameras that will sense during daytime some tailored devices like sticky traps (see fig 1) that attract the insect of interest (but not only), and to fix them on their sticky surface [1]. An on-line video-processing makes it then possible to recognize any trapped insects and describe their spatiotemporal presence which is used to predict a pest attack as previously proposed in [2]. In this paper, we go one step further concerning the performance evaluation of such a system, especially for the insect classification stage. Our goal is to classify mainly two types of harmful insects: mature whitefly (*trialeurodes*) and greenfly (*aphids, less harmful than whitefly*). The shape of both these flies being very similar combined with poor spatial resolution (see fig. 2) due to low-quality optical system and JPEG compression makes it challenging for a classifier to be robust on features based on area, elongation and color. Another problem is light reflection on trap glue. If we have patches from camera saturation parts (see shiny areas on sticky trap in fig. 1), it becomes difficult to discern if it is a whitefly or background. Hence we adopt a two stage procedure in classification. The background color is close to greenfly in color spectrum. So, in the first stage we intend to separate whitefly from greenfly and background samples. Then the samples which are labeled negative (*w.r.t.* whitefly) from the first classifier are fed to another classifier and we make a decision whether we have a greenfly or background.

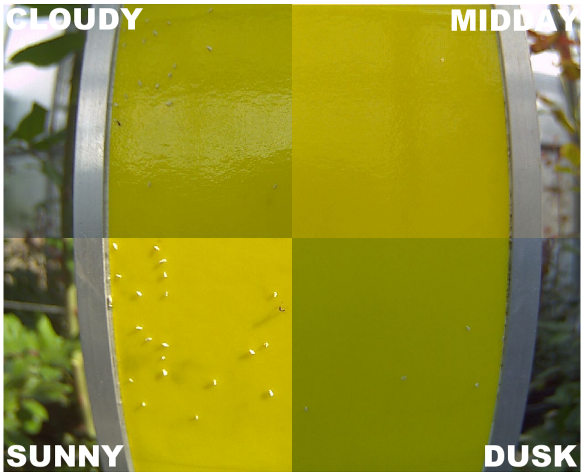


Figure 1: Four mosaic frames from different daytimes. Yellow zone corresponds to the sticky trap & trapped white insects correspond to the tiny spots fixed on its surface.

We set up an experiment with a network of five wireless cameras (protected against water and sun) in a greenhouse of rose plants. The AXIS 207MW video cameras we use provide image resolution of 1280x1024 pixels at 10 fps at most. For reliable counting of harmful insects we keep our real-time to processing one frame per second.
Section 2 describes our approach from detection to classification, while section 3 presents evaluation of results and section 4 summarizes our conclusion.

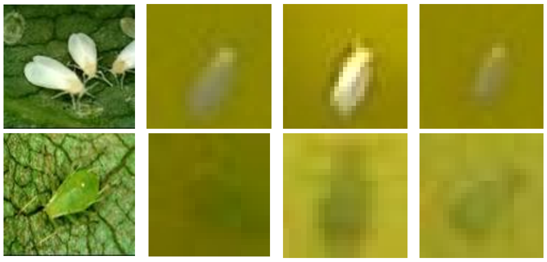
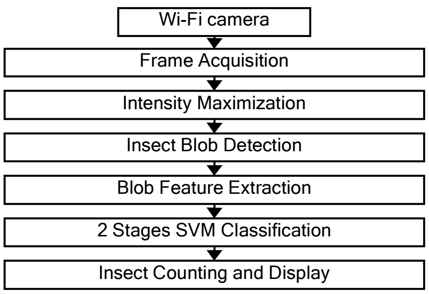


Figure 2: A whitely (first row) and a greenfly (second row) in three different illumination conditions. First column has high resolution images for both flies.

2. Proposed Approach

The workflow of our insect classification and counting is shown in flow diagram below:



2.1 Overview of the Detection Algorithm

The detection algorithm segments pixels of interest in rectangular blobs of different sizes. It uses motion cues based on our observation that the insects move for some time before being glued to the trap. As this is not the main emphasis of this paper, we are not putting much detail for this.

2.2. Data and Pre-Processing

Total number of whitefly samples is 1313; number of greenfly samples is 54 and 950 samples of background. All these samples are of size 21x21 pixels.

Following types of linear transformation are used for the classification:

a. Matlab RGB-to-Gray transformation.

b. Motivated from the fact that the harmful insects of species of interest are characterized by one main color, we use the transformation coefficients which maximize the intensity of whitefly.

The coefficients are estimated in such a way to maximize *w.r.t* linear coefficients the SNR ratio between the mean contrast over a sample of whitefly intensities and the mean contrast over a sample of background intensities.

2.3. Feature Extraction

Three types of feature extraction are used: Color, Gabor filters and Pyramidal Histogram of Gradients.

2.3.1. Colors as Feature

In this case the 3 color channels are directly used as feature vector. We applied Principal Components Analysis (PCA) to reduce feature space dimension.

2.3.2. Log Gabor Filter Bank

Feature extraction using Gabor functions offer simultaneous localization of spatial and frequency information. Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific orientation and at a specific energy. In order to optimally detect and localize features at various scales, a filter bank is constructed where many filters of varying support are used. Apart from number of orientations and scales, the filter parameters to decide on are: filter bandwidth, scaling between center frequencies of successive filters, the angular spread of each filter and the frequencies we want to cover depending on the data. The parameters are tuned so that the filters achieve even spectrum coverage. For four scales and orientation the feature dimension of one sample is 7056. This high feature dimension can bring substantial computation and memory cost to the classifier. So we used the energy and standard deviation of each log-Gabor filter output as feature fed to the classifier. So the feature vector for this case is $(\mu_{11}, \sigma_{11}, .., \mu_{S,O}, \sigma_{S,O})$, where S, O = # of scales and orientations for Gabor filter bank, and σ and μ stands for standard deviation and mean respectively.

2.3.3. Pyramidal Histogram of Gradients (PHOG)

Here the local shape is captured by distribution of edge orientation within a region, and spatial layout by tiling the image into regions of multiple resolutions [3]. Each image is divided into a sequence of increasingly finer spatial grids by repeatedly doubling the number of divisions in each axis direction. The number of points in each cell is then recorded. The cell counts in each level of resolution are bin counts for the histogram representing that level. The PHOG descriptor for an image is either the corresponding HOG vector or a concatenation of all HOG vectors.

In forming a pyramid the grid at level 'L' has 2^L cells along each dimension.

2.4 Insect Classification

The classification is performed with Support Vector Machines (SVM) using LIBSVM library [4]. For color and PHOG features we used RBF kernel while Gabor works best with linear kernel. A five-fold cross validation on training set is performed to get optimal parameters for RBF based SVM classifier.

3. Experimental Results

In the first section here we present the results for the first classifier (differentiating whitefly *w.r.t.* background and greenfly). The second section deals with the second classifier to distinguish between greenfly and background.

3.1 First Classifier Results

The results for the three feature extractors are presented below. Number of training samples in each case is 60 (30 from each set). Test data consist of 1283 whitefly samples, 925 background samples, and 49 greenfly samples. In results columns, Acc. refers to Accuracy, BG stands for background samples while GF stands for greenfly. FPR stands for false positive rate while FNR for false negative rate. PPS refers to number of patches processed in one second by the classifier. This includes feature extraction time also. This is measured on 3.0 GHz CPU, 2GB of RAM equipped computer with Matlab used as development software.

3.1.1 Color as feature vector

PCA is applied to reduce the dimensionality of color feature space. SVD analysis shows that 81% of total variance is retained in 1st 20 principal components (PCs) while total variance retained by 40 PCs is 89%.

	Acc. (%)	FPR (%)		FNR (%)	Feature Dim.	PPS
		BG	GF			
no PCA	89.9	11.4	8.16	9.7	1323	66
20 PCs	90.8	15	50	3.7	20	62

3.1.2. Features from PHOG:

In all the different cases for number of pyramid levels L, SNR maximization whitefly transformation is used to convert the color image to an intensity image.

#L	Acc. (%)	FPR (%)		FNR (%)	Feature Dim.	PPS
		BG	GF			
1-2	93.9	2.5	0	11.6	168	33
2	91.9	2.5	1.8	17	136	38

3.1.3. Energy and standard deviation as features from Gabor filter convolved outputs

In all the cases below SNR maximization whitefly transformation is used to convert the color image to an intensity image.

#S,O	Acc. (%)	FPR (%)		FNR (%)	Feature Dim.	PPS
		BG	GF			
5,4	98.5	1.1	0	1.6	40	25
5,6	98.2	1	0	2.4	60	22

Based on the results above we chose to use Gabor features for the first classifier, as this classifier has the least FNR and FPR.

3.2 Second Classifier Results

For this case we experimented with Gabor features (S=5, O=4, intensity image obtained by Matlab RGB-to-Gray transformation). This classifier is trained with 5 greenfly samples and 5 background samples (our database for greenfly will be enriched after second in-field experiment this May). It identifies 45 out of 49 (91.8%) greenfly samples while 854 out of 910 (93.8%) background samples fed from the first classifier correctly. All the false negative whitefly samples from the first classifier are labeled as greenflies.

3.3 Discussions

Precision/Recall (PR) and ROC curves are presented for the classifier evaluation [5] in fig. 3 & 4. ROC curve is a plot of True Positive Rate (TPR) v/s FPR. In Precision Recall curve Precision is plotted v/s Recall. The goal in ROC space is to be in the upper-left-hand corner, while the goal in PR space is to be on the upper-right-hand corner [5]. The threshold splits are made so that each interval contains same number of sample lines.

Missed samples from PHOG & Color features do contain significant portion of bug inside the blobs and these missed samples are detected correctly by Gabor features.

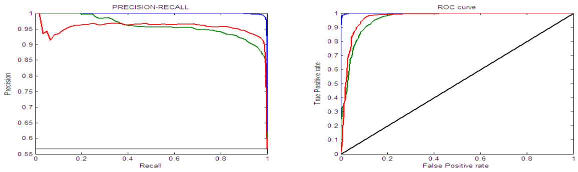


Figure 3: Precision recall and ROC curves for best outputs of the first classifier in terms of total accuracy from different feature extractor: blue- Gabor, green -color, and red - PHOG.

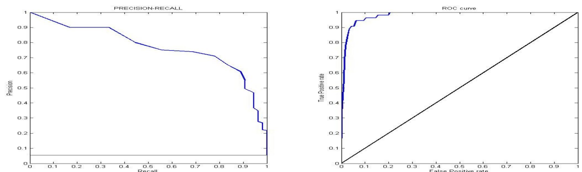


Figure 4: Precision recall and ROC curves for best outputs of the second classifier.

PHOG features do not work well as the nature of background in our case is not flat (*w.r.t.* intensity, see fig 1), so with edge detection we have some random edges for background samples and hence it is difficult to get differentiable shape characteristics.

Gabor features performs the best as compared to other two feature extractors for the problem at hand. The bugs missed by Gabor features were also missed by the other extractors. Missed bugs (False Negatives) are from those blobs in which either there is no insect inside or less than 10% of insect is inside the blob. Improvement of the detection step should figure out this issue. Background samples where the intensity variation is much due to camera saturation resembles some kind of texture are classified as false positives. Concerning the second classifier, since the training data is very small (only 5 samples for each class) there is still room for improvement.

4. Summary and Conclusion

Real-time counting of pests in greenhouse plants is a real challenge in the context of Integrated Pest Management which aims at minimizing the use of pesticides. The decision support system based on video monitoring we propose may be one part of the solution towards early detection of infestations. In this paper, we focus on the insect classification stage. The goal is to robustly classify image patches into whitefly, greenfly, or background samples. We use energy and standard deviation of log-Gabor filter output to fed two SVM classifiers. Parameter optimizations as well as object color enhancing are used to maximize the accuracy of the classifiers. We perform a quantitative evaluation of the classification stage for two harmful pests. Based on the tests out of 1283 whiteflies, we detect 98.5% of them and miss 1.5%. Out of 49 test greenflies we miss 4 samples (8.2%) and detect 91.8%. We label 6% of background samples as greenfly. Finally, 1.5% of whitefly samples are labeled as greenfly. The training set consist of samples from only two frames acquired at only two different times of same day while the test set consist of plenty of samples from different days and daytimes. Our classification approach is then robust to illumination changes while ensuring a low false detection rate. Figure 5 shows one sample frame processed by our classifying software.

Figure 5: Classified regions with red blobs for whitefly and pink for background (no fly regions) and blue are for greenfly. Insect count is displayed to the user. All whiteflies are classified correctly while we have 4 false positives *w.r.t* greenfly count. This is since there are some rare insect which has same shape as greenfly and are of black color.

Future work will concern frame-to-frame tracking and real-time counting applied to the monitoring a greenhouse tomato plant.

References

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