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Automatic detection of bumblebees using video analysis

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Abstract
In this document, we explore and develop techniques to automatically detect bumblebees flying freely inside a greenhouse, where illumination conditions are left unconstrained, and no artifact is used on their bodies. Specifically, we compare a Viola-Jones classifier and a Support Vector Machine (SVM) classifier to detect the presence of bumblebees. Our results show that the latter has a better classification performance.

Keywords: Support Vector Machine classifier; Viola-Jones classifier; bumblebee detection.

Detección automática de abejorros usando análisis de video

Resumen
En este documento exploramos y desarrollamos técnicas para la detección de abejorros que vuelan libremente dentro de un invernadero, en donde las condiciones de iluminación no son controladas y ningún artefacto es colocado en sus cuerpos. En particular, comparamos clasificadores Viola-Jones y Máquinas de Soporte Vectorial (SVM) en su uso para la detección de abejorros. Nuestros datos muestran que el SVM ofrece mejores resultados de clasificación.

Palabras clave: Clasificador tipo Support Vector Machine; Clasificador tipo Viola-Jones; detección de abejorros.

1. Introduction

Pollination is a critical ecosystem service in agriculture [10]. It has been estimated that 75% of human food crops require pollination by insects for adequate production [6,11], bees (Hymenoptera: Apoidea) and bumblebees being the most used in managed pollination programs. To date, bumblebees are used as managed pollinators on more than 40,000 hectares of greenhouses tomato crop in the world [15]. Therefore, monitoring their activity is important from the perspective of ecological research, and when there is the need to know their patterns of activity and how they are affected by greenhouses management practices [5]. Currently, the study of pollination is based fundamentally on direct observations of plant-pollination relationships [8], on offline video monitoring [9,13], and also with the aid of special tags attached to the bumblebees' bodies [3]. Overall, the trend is toward the use of automatic techniques that facilitate biology studies.

The objective of the present document is to report the use of computer vision algorithms to automatically detect the presence of bumblebees, for extended periods of time, and without the need to engineer the environment. To that end, the rest of the document is developed as follow. In Section 2, we survey the related literature. Then in Section 3, we describe the materials and methods used to perform the evaluation. Next, in Section 4, we describe our experimental results. Finally, in Section 5, we conclude the document summarizing our findings and describing potential lines for future research.

2. Related Works

Automatic visual recognition of insects has been used when it has been possible to study static insects, with enough resolution, and in controlled lighting conditions. For instance, Larios *et al.* [7] represent insects by features based on the curvature of their profiles, analyzed on both local and global scales. On the other hand static and adaptive appearance templates for handling appearance change, and geometry-constrained resampling of particles for handling unreliable features has been used in the past [19]. At their end, Yuefang *et al.*[4] identify insects by describing their wings with a combination of moment invariants. In addition, the interaction between insects and the environment can facilitate the use of clustering techniques based on color or intensity, as reported by Jinhui *et al.* [17]. Furthermore, insects can be identified by their traces [12]. Nonetheless, there is a pressing need to increase our understanding for situations where the bumblebees interact freely with their environment.

Detecting and tracking at the beehive entrance has been done in the past making use of computer vision technics in 3D.[20] In our investigation we focus only on the detection of insects either at the entrance of the beehive or at the time of pollination in the flower. Toward that objective, we compare the performance of a Viola-Jones classifier [16] and a Support Vector Machine classifier (SVM) [2]. This work further enhance a previous work [23], where we explored the use of tracking by detection to analyze the arrival of bumblebees to flowers and their motion around beehives.

3. Materials and Methods

A flying cage (6m x 3m x 3m) was covered with an antiaphid net. Inside we placed five tomato (*Solanum lycopersicum*) and Serrano chili (*Capsicum annuun*) flowering plants. A MINIPOL™ (Koppert) hive, containing 30 *Bombus impatiens* (Hymenoptera: Apidae) workers was introduced into the cage two hours before the experiment began. The bumblebees were free to fly inside the cage and a JAI camera model CV-S3200 with an analog interface connected to a National Instrument NI PCI 1411 acquisition board was used to obtain images at a 640 x 480 resolution and a frame rate of 30 fps. Acquisition was done during the day making use of direct sunlight as illumination. The camera was mounted on a metallic support focused at times on a tomato flower as well as to the hive (see Fig. 1). In order to analyze the performance of each classifier, 2,082 images with bumblebees were selected as positive samples and 3,483 without bumblebees as negative samples employing cross-validation. The images included the natural changes of illumination caused by the apparent Sun movement and the occasional Sun occlusion due to clouds. To train the classifiers, we selected 80% of the samples at random using the rest for testing. To construct the Viola-Jones classifier, we used the Open CV library [1], which uses Haar-like features. To construct the SVM classifier, we used the implementation provided by Matlab with a linear kernel, with Histogram of Oriented Gradients (HOG) as features [18]. We constructed Viola-Jones classifiers for 24×24 pixel subimages, with 10, 15, 18, 20, and 22 stages. Their corresponding training time was around 4, 8, 12, 18, and 24 hours, respectively. For the HOG features, we used 64×64 pixel images, with 8×8 pixel cells, and 2×2 cell blocks, as seen in Fig. 3. The SVM works by constructing a feature space where the classes to be distinguished are separated using a certain type of kernel. The search for a bumblebee in a particular image takes place using a hierarchical search of a pyramid structure, where each level has twice the resolution [24]. We accepted bumblebee detection when the Viola-Jones classifier gave a positive response and when the margin of the SVM classifier was positive. We use the Receiver Operating Characteristic (ROC) curve [14] to verify the performance of the classifiers. The computer used for these experiments has an Intel i5 microprocessor with four cores, operating at 3.33GHz, with 8 GB of RAM and running on the Windows 7, 64 bit, operating system.

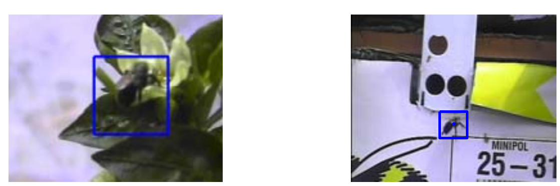
4. Experimental Results

For the Viola-Jones classifier, as the number of stages was varied in the classifier, the performance improved. Fig. 2 illustrates the results as a ROC curve [14]. The reduction of the False Positive Rate (FPR) after the addition of just a few stages in the classifier is remarkable. For instance, the FPR is reduced from ~1.0 to ~0.4 upon changing from a 10-stages classifier to a 15-stages classifier. In fact, the FPR for the 18-stages classifier is 0.04, while the True Positive Rate (TPR) is 0.85. Of course, the TPR decreases accordingly but it does so at a smaller rate. Note that while the TPR is 0.99 with the 10-stages classifier, it is 0.87 and 0.85 with the 15 and 18-stages classifiers, respectively. Similarly, the FPR is below 0.01 for the 20- and 22-stages classifiers, while the TPR is ~0.75. With the SVM classifier, the TPR is 0.98 and the FPR 0.003. These results show a superior performance of the SVM classifier.

5. Conclusion

In this document, we applied Viola-Jones and SVM classifiers to the problem of detecting bumblebees in an unconstrained,green-house-like environment. Furthermore, our results show that the Support Vector Machine classifier, with HOG features, outperforms the Viola-Jones classifier. Managed pollinators like bumblebees are frequently monitored at the hive entrance to determine the foraging activity rate by counting the number of bees coming in or out the hive [21]. This activity rate is an important element of practical pollination studies in greenhouses [22]. A system counting automatically the number of bees flying in and out of the hive or the number of bumblebees arriving to a flower with high accuracy would be very informative. However, in some computer vision systems the illumination changes could affect the outcome of the detection. HOG features are less affected by possible illumination changes, because they are based on the orientation of gradients and the normalization of image blocks. Keeping the natural illumination conditions is important in order not to disturb the behavior of bumblebees. More research should increase the performance of the detectors, highlight other aspects of the insect-pollinators activity, and lead the development of more flexible monitoring tools. For instance, a possible way to increase the performance of either one of the classifiers could involve the use of a detection-and-tracking strategy. Such strategy could be used in combination to fill the gaps whenever a bumblebee is not detected.

6. Figures



(a) (b)

Figure 1. Bumblebee detection scenarios. (a) When the bumblebees visit flowers, and (b) flying in and out their beehive.
Source: The authors

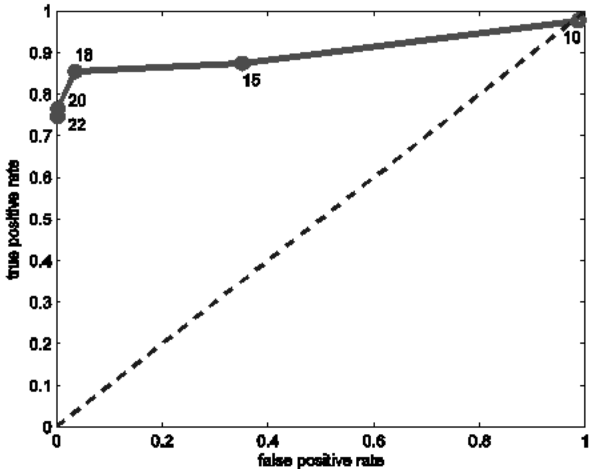


Figure 2. Viola-Jones classifier performance. The solid red line indicates the performance of the Viola-Jones classifiers for a different number of stages. The numbers around the circles in the solid line inform the number of stages.
Source: The authors

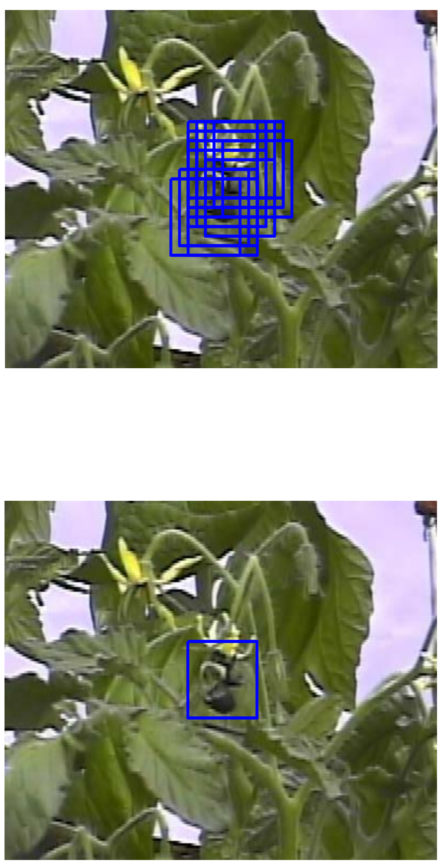


Figure 3. Bumblebee detection using the SVM classifier. (a) Blue squares correspond to the 64 x 64 pixel subimages classified as positive samples in the whole image, and (b) in each group of adjacent squares, only the one with the features mapped farther to the hyperplane used for classification is kept and the others are filtered out.
Source: The authors

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