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Automatic Detection of Field-Grown Cucumbers for Robotic Harvesting

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ABSTRACT The objective of the research presented in this paper was to design an accurate and robust algorithm for the challenging task of detecting field-grown cucumbers for robotic harvesting automation in precision agriculture applications. The proposed algorithm is based on a combination of several processing and data mining techniques to achieve a classification system capable of segmenting cucumbers from the different elements of the scene, such as leaves, stems, the ground, stones, and irrigation pipes. The algorithm includes a support vector machine pixel classifier that provides the initial regions of interest for further processing, a Euclidean distance transform for eliminating less compact blobs that usually correspond to flowers and young leaves, an image category classifier based on a bag-of-visual-words model that increases the detection reliability, and a segmentation procedure based on the watershed transform and the minima imposition technique. Several experimental campaigns were carried out in field conditions to acquire data for training the classifiers and for validating the designed algorithm. Detection performance was evaluated at both the pixel and cucumber levels by comparing the results provided by the proposed algorithm with the ground truth data generated from hand-labeled images. The high hit rate and the low false-positive rate obtained at the pixel level and the high recall and precision at the cucumber level demonstrated the satisfactory performance of the proposed solution and highlight its potential benefits for automatic cucumber-harvesting applications.

INDEX TERMS Robot vision system, precision agriculture, grown-field cucumbers, automatic detection, image processing, robotic harvesting, machine learning, SVM, bag-of-visual-words.

I. INTRODUCTION

In 2016, the global production of cucumbers and gherkins worldwide was $80.6 \cdot 10^9$ kg, ranking the vegetables third in terms of volume of total production after tomatoes and onions. This statistic demonstrates the global importance of cucumbers and gherkins agriculturally and economically. In the same year, the production of cucumbers and gherkins in the European Union amounted to $6.4 \cdot 10^9$ kg, representing 7.9% of total global production [1]. However, the production trend in recent years (see Fig. 1) indicates a significant slowdown in the growth of the European Union's cucumber production, marked by (i) high labor costs, which reduce profitability and the competitiveness of the products; (ii) the strong emergence of countries with competitive advantages such as low costs of land and low wages; (iii) and the growing difficulty in finding a workforce, due to the high seasonality of jobs, harsh working conditions and scarce attractiveness as harvesting is considered a low-skilled job. In addition, the growth rate of cucumber fruits is high, requiring the fruits to be harvested two or three times a week. This high frequency is one reason why the harvesting of cucumber is more labor-intensive than that of any other vegetable fruit [2].

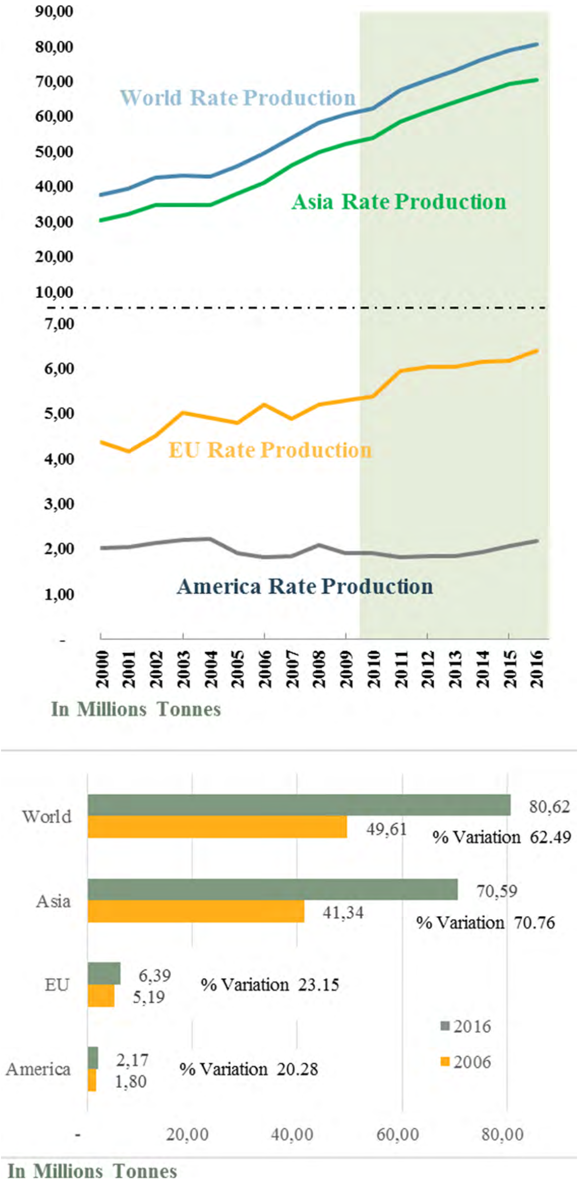


FIGURE 1. **World cucumber map. Evolution of cucumber and gherkin production in recent years. Data extracted from FAOSTAT.**

These findings highlight the need to design common strategies to strengthen the sector and thereby improve the efficiency of the processes involved in these activities. Service robots are becoming a key part of many sectors of society, including precision agriculture, where they are called upon to play an important role in improving competitiveness and sustainable production [3].

Thus, one of the most promising approaches for improving agricultural production yields is the use of autonomous harvesting robots. An important first step in the development of any automated harvesting robot is the design of a sensory system that provides reliable data that can be processed and analyzed to detect the presence of fruits, discriminating them from the rest of the scene elements. However, the automatic detection of cucumbers in natural scenes is quite challenging. Cucumbers are highly similar in color to leaves and stems. In addition, most cucumbers are partially occluded by leaves or stems or overlapped with other fruits. These occlusions eliminate the direct correspondence between visible areas of cucumbers and cucumbers themselves by introducing ambiguity into the interpretation of the shape of occluded cucumbers [4]. Unlike cucumbers grown in greenhouses with a relatively uniform layout, field-grown cucumbers can be found in quite random positions and orientations and in various sizes, volumes and limb structures. The variable environmental conditions inherent to outdoor scenarios also magnify the technical challenge imposed on a sensory system.

Over the past two decades, several studies have been conducted to provide automatic detection and measurement systems for different features of cucumbers crops. One of the first studies in this area was [5], in which an image analysis method was proposed for the automated assessment of the length and width of cucumber fruit, as well as the length and shape of the neck of the fruit. Cucumber fruits were placed on an illumination table equipped with background lighting, and a CCD video camera mounted perpendicularly above the table was used for image acquisition. Van Henten *et al.* [6] proposed a combination of two CCD cameras, one equipped with an 850 nm filter and the other with a 970 nm filter for detecting cucumber fruits grown in greenhouses using a high-wire cultivation system, in which every plant is attached to a wire. Experimental tests showed that the designed system was able to detect more than 95% of the fruits in a dataset of 106 cucumbers, with 19 false positives. Image acquisition was carried out such that every part of the plant stand appeared three times in the camera's field of view but from different perspectives. If a cucumber was detected in at least one of the three images, it was counted as detected. A segmentation algorithm based on rough set theory was presented in [7] for solving the problem of cucumber identification in greenhouses. However, no quantitative results derived from the proposed algorithm were presented. In [8], a three-layer back-propagation neural network combined with a texture analysis was established to detect greenhouse cucumber fruits. The algorithm was tested on 40 cucumber plant images, and a detection rate of approximately 76% was achieved considering only backlighting conditions. A simplified pulse-coupled neural network algorithm was proposed by Wang *et al.* [9] for segmenting greenhouse cucumbers from a complex background. The connection strength coefficients were adjusted adaptively by using the local standard deviation. The rate of correct segmentation obtained from the experimental results was approximately 82.4%. More recently, deep convolutional neural networks have been proposed for detecting other fruits, such as mangoes [10], sweet peppers and rock melons [11], exhibiting promising results with F1 scores of 0.881 and 0.838, respectively. In [12], Noble and Li presented schemes for classifying cucumber fruits, leaves, and vines under laboratory conditions and greenhouse conditions, concluding that the utilization of the water absorption band at 970 nm is generally effective for segmenting cucumber fruits from images. However, the quality of the segmentation is highly dependent on illumination. No quantitative results were presented. Clement *et al.* [13] proposed a computer algorithm based on active contours to classify cucumbers by length and curvature. The system uses digital imaging technology operating within the visible spectrum. A multi-template matching method was utilized by Bao *et al.* [14] to recognize matured Radit cucumbers grown vertically in a greenhouse. Proportional scaling and rotation operations were applied to a standard cucumber image to build a multi-template matching library, whereas the multi-template matching method was developed by using the normalized correlation coefficients algorithm. For evaluation, images were shrunk to a size of 240×180 pixels, with a target in the center of the image. In total, 100 images were analyzed and 98% of the cucumbers were correctly recognized. In [15], a Kinect sensor was used to acquire greenhouse cucumber images, which were segmented based on a color and region growing algorithm. The targets contours were then extracted and the feature values of the tangent point and the centroid were calculated. The algorithm was validated in a collection of 4 cucumber photos, providing a segmentation success rate without occlusions of almost 100%.

This paper presents research carried out to design and implement an accurate and reliable algorithm for detecting field-grown cucumbers from an RGB image. The proposed solution is intended to be used in autonomous harvesting robotic systems and differs from all previous approaches found in the literature, which mainly focus on the detection or characterization of cucumbers grown in greenhouses by using wire cultivation systems. Cucumbers grown using wire cultivation systems are less prone to the formation of clusters of overlapping cucumbers, less affected by occlusions, and feature a fairly well-defined orientation with respect to the plants, simplifying detection.

In addition, the proposed sensory rig is based solely on an RGB camera, which decreases the total cost of the system and makes the future harvesting robot in which it is incorporated more competitive in the market.

The rest of the paper is organized as follows. Section 2 describes the design and implementation of the proposed detection algorithm. Section 3 presents the results obtained from the different experimental tests carried out. Section 4 discusses the main results of this work, and finally, Section 5 summarizes the main conclusions.

II. MATERIALS AND METHODS

A. STUDY SITE

Data acquisition was conducted in several experimental campaigns between June and August of 2017 under field conditions in Arganda del Rey - Madrid, Spain (lat. 40°18'58.1''N; long. 03°29'5.5''W). This timeframe allowed us to acquire images at different growth stages of the cucumber plants. The experimental field was planted with Quirk cucumbers, a new variety developed by the seed producer Ryk Zwaan GmBH for the CATCH experiment within the FP7 EU project ECHORD++. This new variety is characterized by providing small, pale cucumbers.

B. PRELIMINARY HYPERSPECTRAL STUDY

Before initiating the design of the detection algorithm, a preliminary hyperspectral study was carried out to determine the wavelengths that could be relevant for the discrimination of cucumbers with respect to other elements of the plant, such as the leaves. To that end, several samples of cucumbers and leaves of the Quirk cultivar were scanned with a pushbroom hyperspectral system, which consisted of an objective lens, an ImSpector V10E spectrograph, a Pulnix TM-1327GE CCD camera and a DC-regulated 150 watt-halogen light source that provided intense, cold illumination. This system enabled recording of 200 spectral bands in the visible and near-infrared regions between 400 nm and 1000 nm, with 3 nm between contiguous bands. Fig. 2 shows the resulting images for leaves and cucumbers at 470 nm, 534 nm, 685 nm, 720 nm and 755 nm. With the acquired information, we obtained the corresponding signatures for the leaves and cucumbers of the Quirk cultivar (see Fig. 3). These signatures confirmed that the reflectance ratios of cucumbers-to-leaves in the visible region provide sufficient differences for discrimination. Therefore, we discarded the use of a sensor operating in a specific wavelength and looked for a simple RGB camera.

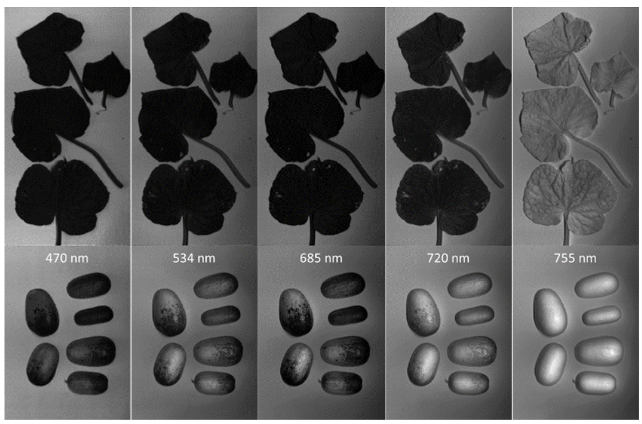


FIGURE 2. Narrow-band images of cucumbers and leaves from the Quirk cultivar at 470 nm, 534 nm, 685 nm, 720 nm and 755 nm.

C. VISION SYSTEM

An AVT Prosilica GC2450 camera (Allied Vision, Stradtroda, Germany) was utilized to acquire high-resolution color images, which were supplied as input for the detection algorithm. The AVT Prosilica GC2450 color camera was installed in a Bosch frame such that the image plane was parallel to the ground plane. The distance between the frontal plane of the camera and the ground was approximately 700 mm.

D. METHOD

This section describes the various steps of the processing algorithm designed and implemented for the automatic

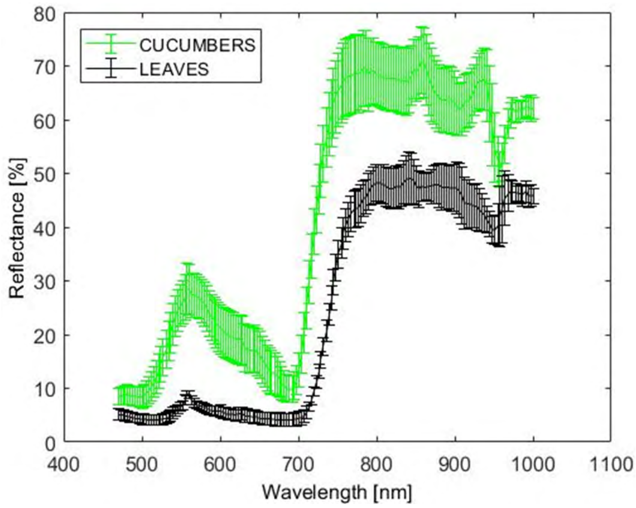


FIGURE 3. Spectral signatures.

detection of field-grown cucumbers. The proposed algorithm combines a support vector machine (SVM) pixel classifier that provides the initial regions of interest for further processing, a Euclidean distance transform for eliminating less compact blobs that usually correspond to flowers and young leaves, an image category classifier based on a bag-of-visual-words model that increases the detection reliability, and a segmentation procedure based on the watershed transform and the minima imposition technique (see Fig. 4).

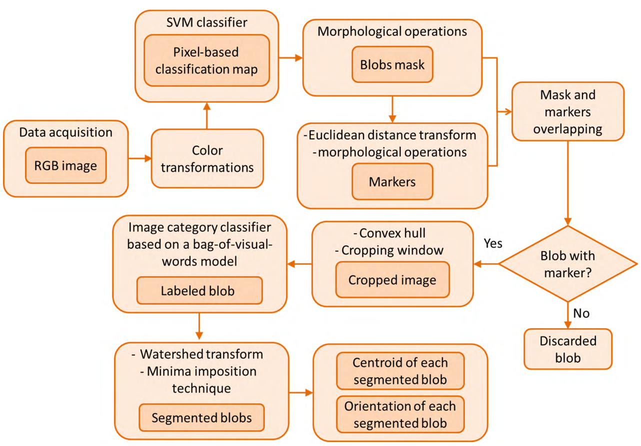


FIGURE 4. Overview of the proposed detection algorithm.

The desired outputs are the centroids of the visible areas of the cucumbers present in the acquired images, as well as their corresponding orientations, which are given by the angles between the x-axis and the major axes of the ellipses that have the same normalized central moments as the regions of interest.

As a first step, a multiclass SVM classifier is trained on color information to identify the initial regions of interest [16], [17]. As the proposed solution is intended to be used with a cucumber harvesting robot, a multiclass SVM machine classifier is preferred over a binary SVM since detection of leaves is important for the trajectory planning of arms and grippers. Instead of directly using the original R, G, and B values, color transformations are introduced before applying the SVM classifier to make the algorithm response less sensitive to changing illumination conditions. These transformations quantify the intensity difference between green and blue (G-B) and the proportion of green (G/(R+G+B)) in the RGB color model and quantify the hue in the HSV (hue saturation value) color model (see Fig. 5). Two acquired datasets were randomly selected for training the SVM of the proposed classification algorithm. After applying the color transformations described above, 15 representative regions of interest of different sizes were selected for each desired class. The mean reflectance values of these regions were then treated as training samples and were manually labeled into three semantic classes: cucumbers, leaves and background, providing a set of 135 observations (45 observations per class). With the obtained set of samples per class, the SVMs of the proposed algorithm were trained to classify the pixels of the images by using a linear kernel function and the one-versus-one coding design.

The resulting pixel-based classification map (see Fig. 6-(a)) was then utilized to generate a mask enabling us to work only with those pixels that belonged to the cucumber class in the next processing steps and discard the rest. Thus, only pixels classified as cucumbers were retained, and two morphological operations were applied: an area opening to remove all connected components with fewer than 550 pixels and a flood-fill operation to fill in holes. With this set of morphological operations, all areas with a small number of pixels in the background were removed and small holes within the cucumbers were filled in (see Fig. 6-(b)). These small holes within the cucumbers correspond to areas overexposed to light.

During the design of the proposed algorithm, we observed that the resulting pixel-based classification map provides a high true detection rate for the cucumber class. However, we also found that young leaves and flowers frequently produced numerous false positives due to their similar colorations. A more detailed comparison of correctly and incorrectly classified blobs demonstrates that those blobs that belong to cucumber fruits are always denser and more compact than those corresponding to young leaves and flowers. This discrepancy is mainly due to the uniformity of the cucumber fruits, in contrast to the irregular surface of leaves and flowers. Therefore, to discard these incorrectly classified blobs automatically, we computed the Euclidean distance transform of the binary image obtained from the previous step (see Fig. 6-(c)). With this nearest-neighbor distance criterion, it is possible to identify pixels that belong to one object, as the value of each pixel in the derived representation is replaced by its distance to the nearest background pixel [18]. Next, Otsu's method [19] is applied to choose a global threshold that minimizes the intraclass variance of the distance pixels. With the attained threshold, a binarization of the distance image is conducted, followed by a dilation of

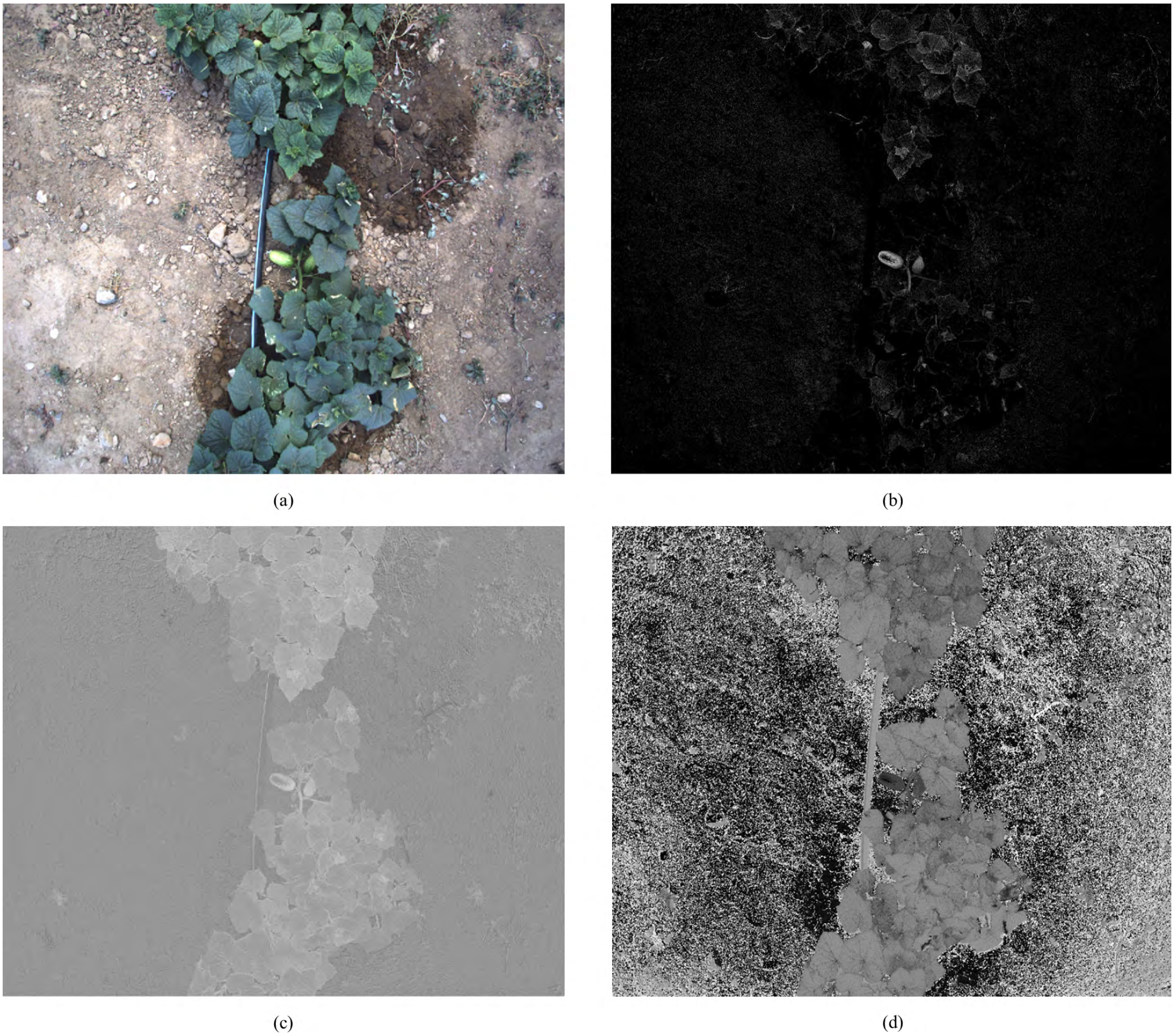


FIGURE 5. **Experimental results – Test 1. (a) Original RGB image; (b) intensity difference between green and blue; (c) proportion of green; and (d) hue component of the HSV color space.**

the background region and a morphological operation for discarding small blobs that correspond to leaves and flowers and that consequently produce detection errors. Then, a marker is created for each of the remaining blobs that are candidates for representing a cucumber fruit (see Fig. 6-(d)). These markers are overlapped with the mask resulting from the classification map (see Fig. 6-(b)), and only those blobs marked are retained for further processing. Next, we compute the convex hulls of all the preserved blobs (see Fig. 7-(a)).

To further increase the robustness of the detection algorithm, each blob retained from the previous step is analyzed to confirm whether it is a cucumber. To that end, an image category classifier [20] is implemented by using a bag-of-visual-words model [21], [22] (see Fig. 7-(b)). The model requires a vocabulary of representative descriptors for each image category. These descriptors are used as references for quantifying features in the images. In the proposed case, the descriptors are created by extracting Speeded-UP Robust Features (SURF) [23] from an acquired dataset that includes 15 images for each of the following categories: cucumbers, flowers, leaves, stems and background. Point locations are selected on a predefined grid with spacing [8 8]; that is, a uniform grid with steps of 8 pixels in the x and y directions. Locations for feature extraction are then defined by the intersections of the grid lines. By keeping 80% of the strongest features from each category and balancing the number of features across all image categories to improve clustering, the strongest 5161 features from each of the image categories are obtained. A visual vocabulary of 500 words is then constructed by reducing the number of features through

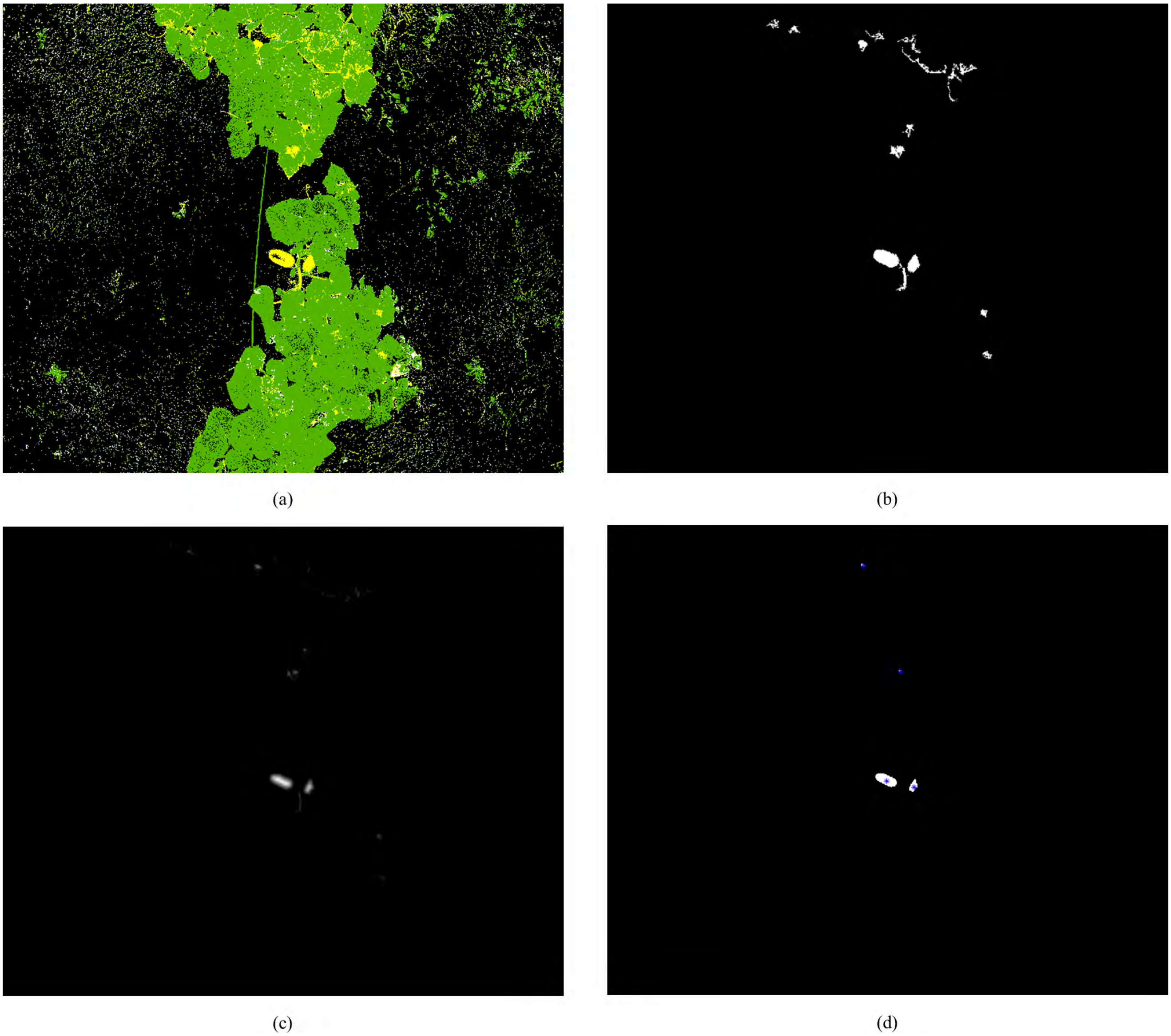
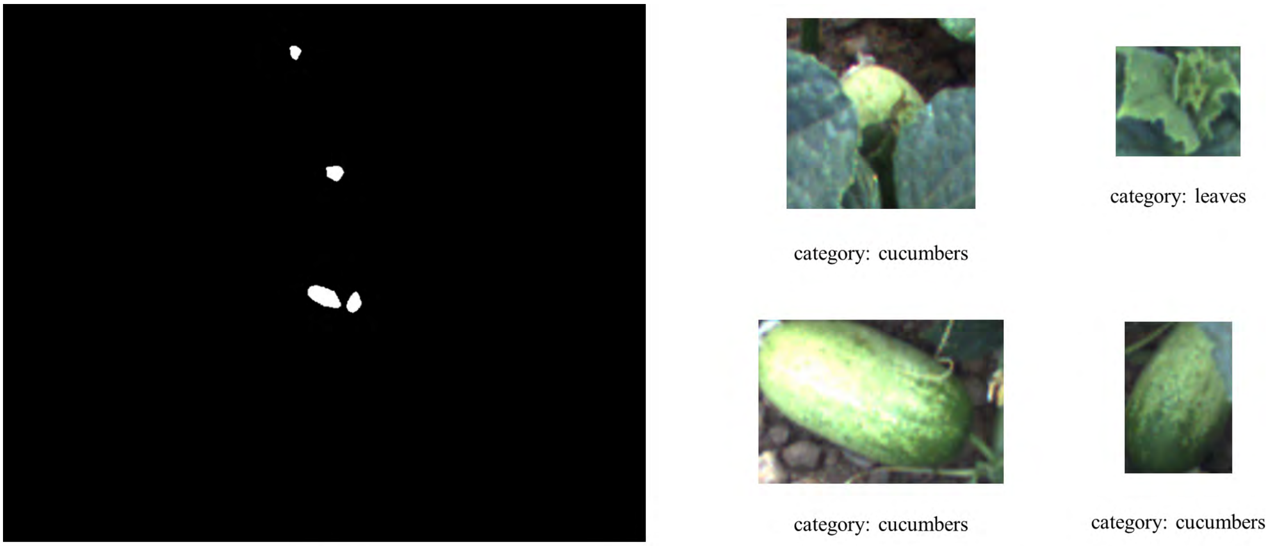


FIGURE 6. **Experimental results – Test 1. (a) Pixel-based classification map; (b) mask obtained after morphological operations; (c) result of applying the Euclidean distance transform; (d) blobs marked as possible cucumbers.**

the quantization of the feature space using K-means clustering [24], [25]. The resulting clusters are compact and separated by similar characteristics. Each cluster center represents a visual word. Additionally, the visual word occurrence in each image is counted and encoded in a histogram that becomes the new and reduced feature vector representation of the image. In this manner, the bag-of-visual-words model represents each image by a frequency distribution of its visual vocabularies. An SVM classifier is then trained to discriminate between vectors corresponding to positive and negative training images. Both the bag-of-visual-words model and the SVM training are carried out offline.

To transform the selected polygonal regions into input images for the category classifier, the exterior boundaries of the blobs are traced and a cell array of boundary pixel locations is generated. For each cell, the minimum and maximum values of x and y are found, and these pairs of minimum and maximum coordinates are then utilized to crop the original color image around each blob. Because the cropped image should provide sufficient information for recognition, the minimum size used for the cropping window is 100 pixels $\times$ 100 pixels. This size was selected based on the average size of cucumber templates. Thus, if a blob is large enough to be categorized, the pair of minimum and maximum coordinates is used to crop the image. Otherwise, the defined window is centered on the blob centroid and utilized to crop the image. After this step, the proposed image category classifier returns the labels of the cropped images.

Next, a logical AND between the cropped images categorized as cucumbers and the mask of blobs obtained from the



(a) (b)

FIGURE 7. **Experimental results – Test 1. (a) Convex hulls of marked blobs; (b) images utilized as input for the category classifier based on a bag-of-visual-words model and the corresponding output labels.**

pixel-based classification map is conducted. In this manner, only pixels belonging to the cucumber category are preserved. It is then necessary to check whether the preserved blobs are formed by one or several overlapping cucumbers. To accomplish this, a segmentation based on the watershed transform [26]–[28] is applied to all the blobs that have been categorized as cucumber and have an area greater than 8000 pixels. This minimum area size was selected based on the average size of cucumber templates. Watershed transformation is an effective morphological tool that treats an image as a topographic surface, providing catchment basins and watershed ridge lines by assuming that any object is characterized by a homogeneous texture and hence a weak gradient. Therefore, the objects in an image correspond to the minima of the morphological gradients and their contours to the watershed of the gradient [29], [30]. Considering the prior knowledge about the cucumber image structure, some changes are introduced into the preserved blobs to avoid local minima that can lead to over-segmentation. First, a morphological operation is applied to remove stray isolated pixels. Then, the Euclidean distance transform is computed to find foreground markers inside each of the cucumbers. Because a typical image of overlapping cucumbers consists of roughly ellipsoidal, touching blobs, the Euclidean distance transform is useful for producing catchment basins in the cucumbers that should be identified. Next, small local minima are filtered out by using the extended-minima transform, and the Euclidean distance transform is modified with the minima imposition technique such that no minima occur at the filtered-out locations [31], [32]. After these steps, the watershed transform is computed, and the resulting watershed ridge lines are utilized to segment the blobs. Finally, we calculate the centroids and the angles between the x-axis and the major axes of the ellipses that have the same normalized central moments as the segmented blobs (see Fig. 8).

FIGURE 8. **Results provided by the proposed detection algorithm: centroids and ellipses of the blobs detected as cucumbers.**

III. RESULTS AND VALIDATION

A. EXPERIMENTAL RESULTS

The images acquired during the experimental campaigns were crucial for obtaining initial intuitive insights regarding the data to be confronted by the detection algorithm, for training the SVMs and generating the vocabulary of the bag-of-visual-words model, and finally, for the empirical evaluation and testing of the proposed detection algorithm.

In the following, two tests are presented to illustrate most of the intermediate results obtained from the different steps

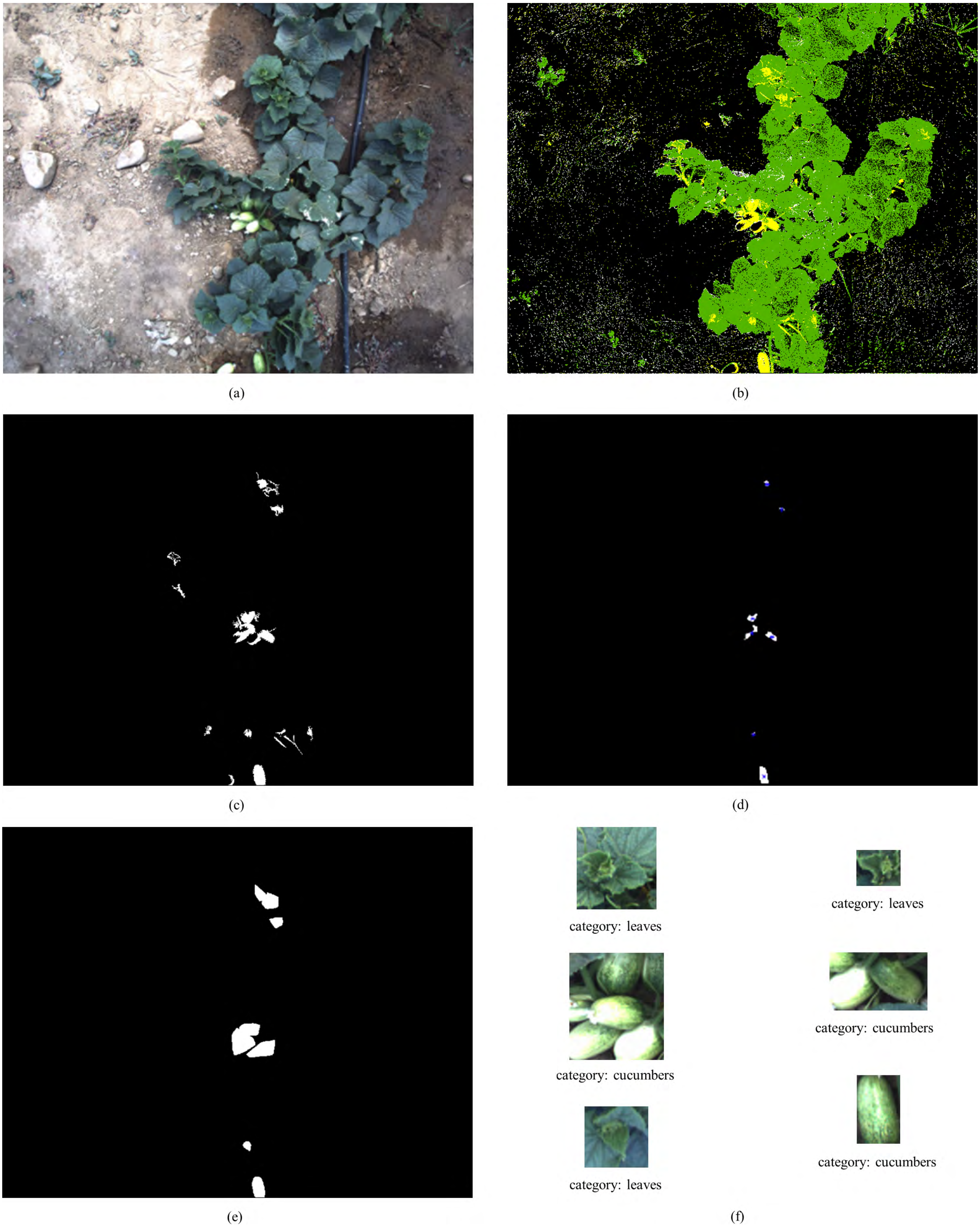


FIGURE 9. **Experimental results – Test 2. (a) Original RGB image; (b) pixel-based classification map; (c) mask obtained after morphological operations; (d) blobs marked as possible cucumbers after applying the Euclidean distance transform; (e) convex hulls of marked blobs and (f) images utilized as input for the category classifier based on a bag-of-visual-words model and the corresponding output labels.**

of the proposed algorithm for the detection of field-grown cucumbers at different stages of plant growth.

1) PLANTS FEATURING FEW ISOLATED CUCUMBERS

This first test is illustrated in Figs. 5-8. Fig. 5 displays (a) the original RGB image acquired in the field with the Prosilica camera, (b) the intensity difference between the green and blue channels, (c) the proportion of green in the RGB color model and (d) the hue component of the HSV color model. The last three images obtained from the described color transformations are utilized as inputs for the SVM classifier.

The pixel-based classification map resulting from the SVM classifier is shown in Fig. 6-(a). In this map, pixels classified as cucumbers, leaves and background are shown in yellow, green and black, respectively. Fig. 6-(b) displays the mask obtained from the pixels classified as cucumbers, after applying morphological operations for both removing noise and filling small holes within the cucumbers. In Fig. 6-(b), it becomes clear that blobs that correspond to cucumber fruits are denser and more compact than those belonging to young leaves and flowers. For this reason, we computed the Euclidean distance transform of this image, as illustrated in Fig. 6-(c). Then, a binarization of the distance image, a dilation of the background and a morphological operation for removing areas with a small number of pixels were conducted to discard some of the incorrectly classified blobs. Fig. 6-(d) displays the results of these procedures, as well as the markers created for each remaining blob that is a potential cucumber candidate. These markers are overlapped with the mask presented in Fig. 6-(b), and only those blobs marked were retained for further processing. Fig. 7-(a) shows the convex hulls of the marked blobs that were preserved.

Fig. 7-(b) displays the images cropped for each preserved blob. These images are utilized as input for the image category classifier implemented by using a bag-of-visual-words model. Fig. 7-(b) also presents the resulting labels provided by the classifier. Notably, all cropped images are correctly classified, thus increasing the robustness of the detection algorithm.

Fig. 8 shows the resulting centroids and ellipses, which have the same normalized central moments as the blobs categorized as cucumbers. Thus, in this example, all areas of visible cucumbers are detected successfully with the proposed algorithm.

2) PLANTS FEATURING CLUSTERS OF CUCUMBERS

The second test, shown in Figs. 9-12, corresponds to a more advanced stage of development. In this case, Fig. 9 displays (a) the original RGB image, (b) the pixel-based classification map, (c) the cucumber mask, (d) the markers created after the Euclidean distance transform, (e) the convex hulls of the preserved blobs, and (f) the labels provided by the image category classifier. Once again, in this test, all cropped images are correctly classified.

Because two of the blobs consist of cucumber clusters with areas greater than the predefined threshold in this case,

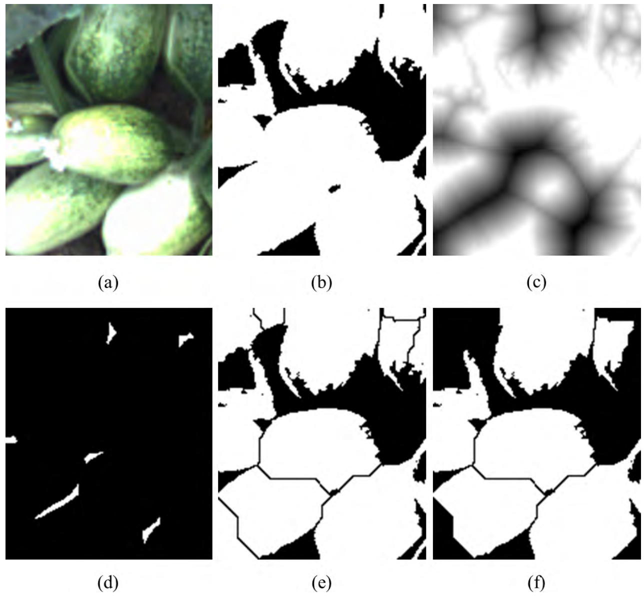


FIGURE 10. Test 2. (a) Input image; (b) morphological operations; (c) Euclidean distance transform; (d) foreground markers; (e) watershed transform; and (f) blobs resulting from the segmentation procedure.

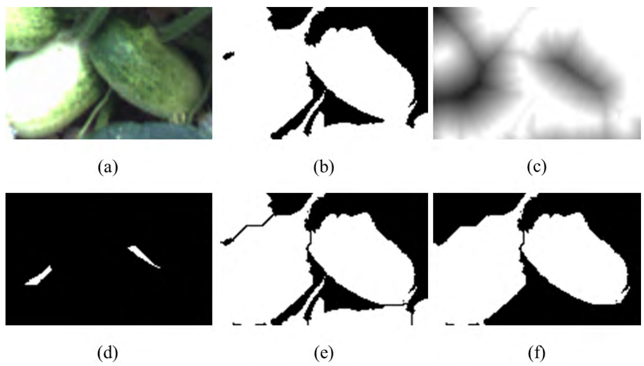


FIGURE 11. Test 2. (a) Input image; (b) morphological operations; (c) Euclidean distance transform; (d) foreground markers; (e) watershed transform; and (f) blobs resulting from the segmentation procedure.

in Figs. 10 and 11, we present the results of the segmentation procedure based on the watershed transform and the minima imposition technique. Figs. 10-(a) and 11-(a) show the images used as inputs for the segmentation procedure. Figs. 10-(b) and 11-(b) display the images obtained after a binarization and the application of a morphological operation to remove stray isolated pixels. The results of computing the Euclidean distance transform for these images are illustrated in Figs. 10-(c) and 11-(c). Foreground markers obtained with the minima imposition technique are presented in Figs. 10-(d) and 11-(d). Figs. 10-(e) and 11-(e) show the results of the watershed transform, whereas Figs. 10-(f) and 11-(f) display the blobs resulting from the segmentation procedure. Note that only the blobs segmented by the watershed transform that contain a foreground marker are considered cucumbers. Finally, Fig. 12 shows the resulting centroids and ellipses that have the same normalized central moments as the blobs categorized as cucumbers. Although in

TABLE 1. Performance results of the intermediate processing step based on the SVM classifier.

Values	TPR	FPR	FNR
Mean	84.45%	2.86%	15.54%
Minimum	24.03%	0.36%	0.46%
Maximum	99.53%	7.37%	75.96%

TABLE 2. Performance assessment at the pixel level of the proposed detection algorithm.

Values	TPR	FPR	FNR
Mean	91.79%	2.56%	8.21%
Minimum	68.39%	0.36%	0.38%
Maximum	99.62%	6.14%	31.61%

FIGURE 12. Results provided by the proposed detection algorithm: centroids and ellipses of the blobs detected as cucumbers.

this case one of the cucumbers is missed, the results are quite satisfactory in terms of detection and segmentation.

B. VALIDATION

To evaluate the performance of the proposed detection algorithm quantitatively, ground truth data were carefully produced for 45 scenes. This process included the manual labeling of the pixels that belong to the visible areas of the cucumbers, as well as the calculation of the centroids and the angles between the x-axis and the major axes of the ellipses that have the same normalized central moments as the visible areas of the cucumbers. Fig. 13 shows the ground truth generated for the RGB images presented in Figs. 5-(a) and 9-(a).

Thus, the quality of the proposed detection algorithm is rated by comparing the obtained detection results with the generated ground truth data, which are used as reference values. The assessment is then divided into the following three levels.

First, detection performance is evaluated at the pixel level in terms of the true-positive rate, false-positive rate and false-negative rate [33], [34].

The true-positive detection rate is defined as the proportion of pixels that are correctly identified as cucumber:

$$\mathrm{TPR} = \frac{\mathrm{n}^\circ \text{ of pixels correctly identified as cucumber}}{\text{total number of actual cucumber pixels}} \tag{1}$$

The false-positive detection rate, which is the proportion of pixels that are incorrectly classified as cucumber, is calculated as follows:

$$\mathrm{FPR} = \frac{\mathrm{n}^\circ \text{ of pixels incorrectly identified as cucumber}}{\mathrm{n}^\circ \text{ of pixels of other classess (not cucumber)}} \tag{2}$$

The false-negative rate, which is the proportion of cucumber pixels that are not classified as cucumber, is calculated as follows:

$$\mathrm{FNR} = \frac{\mathrm{n}^\circ \text{ of cucumber pixels identified as not cucumber}}{\text{total number of actual cucumber pixels}} \tag{3}$$

Table 1 shows the performance results of the intermediate processing step based on the SVM classifier, whereas Table 2 summarizes the performance assessment of the proposed detection algorithm at the pixel level. In both cases, the mean values obtained from all the analyzed scenes as well as the minimum and maximum values are presented.

Next, the proposed detection algorithm is evaluated at the cucumber level in terms of recall, precision and F-score. In this case, instead of counting the pixels, the cucumbers are counted as units.

Recall or TPR is the proportion of detected cucumbers that are actual cucumbers and is given by:

$$\text{Recall or TPR} = \frac{tp}{tp + fn}, \tag{4}$$

where tp is the number of correctly identified cucumbers, and $tp + fn$ is the total number of cucumbers.

Precision is the ratio of correctly identified cucumbers to the total number of identified cucumbers and is calculated as follows:

$$\text{Precision} = \frac{tp}{tp + fp}, \tag{5}$$

where fp is the number of identified cucumbers that are not actually cucumbers.

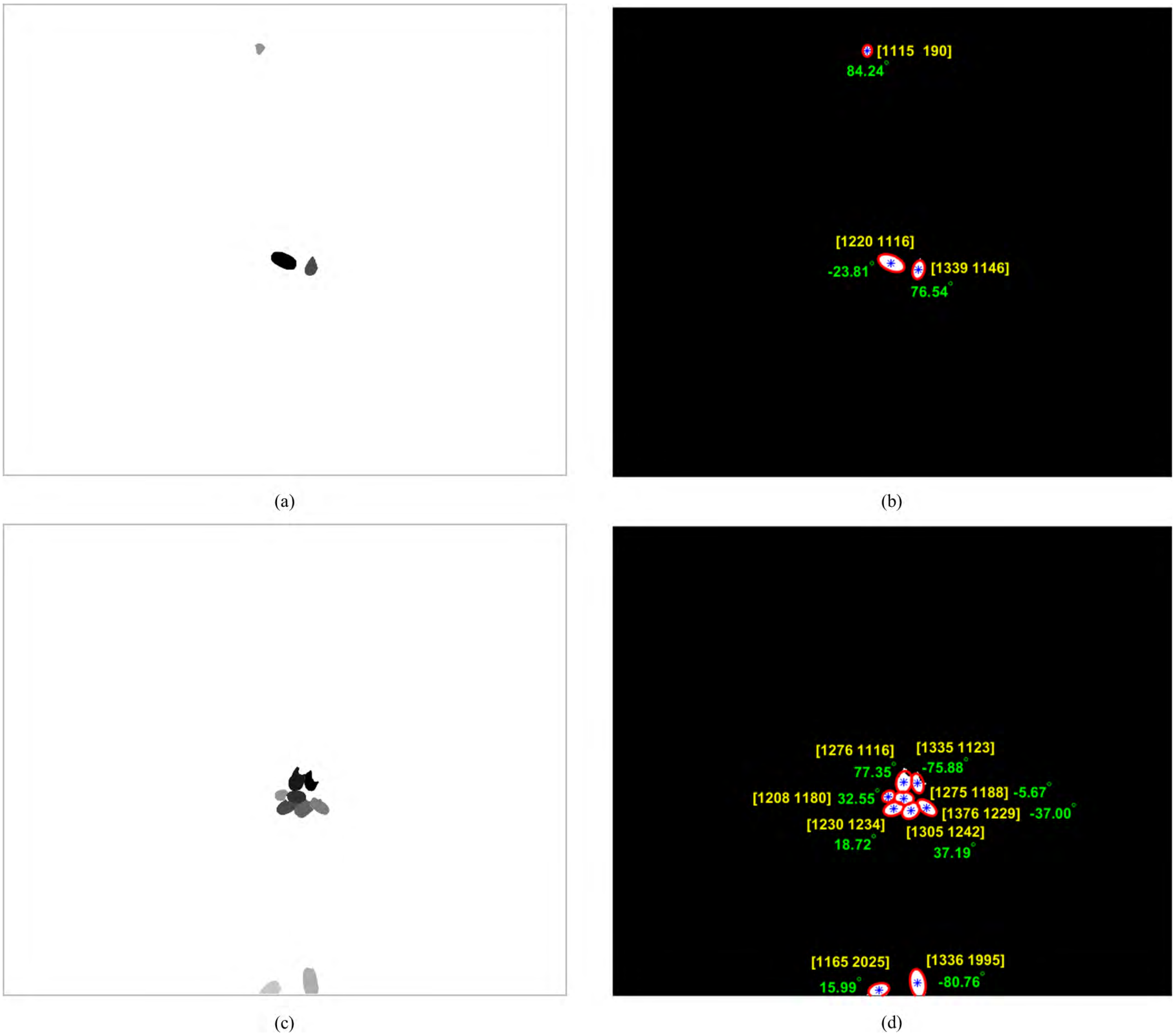


FIGURE 13. **Ground truth. (a) Pixel labeling for Fig. 5-(a); (b) calculated centroids and angles for Fig. 5-(a); (c) pixel labeling for Fig. 9-(a); and (d) calculated centroids and angles for Fig. 9-(a).**

TABLE 3. **Performance evaluation at cucumber level.**

Recall	Precision	F-score
90.10%	85.65%	0.878

The F-score is the weighted harmonic mean of the recall and precision. In this case, recall and precision are given equal weight and the F-score can therefore be referred to as F_1. The F-score is then calculated as follows:

$$\text{F-score or } F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}, \tag{6}$$

Table 3 shows the mean values obtained from all the analyzed scenes.

Finally, it is necessary to assess the performance of the proposed detection algorithm from the perspective of cucumbers segmentation as well as the estimation of the visible areas of the cucumbers and their corresponding orientation on the image plane. To that end, the mean absolute errors of the centroid position and the orientation are selected as performance metrics. The mean absolute error of the centroid position is given by the average of the absolute differences between the true coordinates of the centroids of the visible areas of the cucumbers manually labeled in the ground truth images and the corresponding coordinates of the centroids of the blobs detected by the proposed algorithm. Similarly, the mean absolute orientation error is calculated as the average of the absolute differences between the orientations of the visible areas of the cucumbers manually labeled in the ground

TABLE 4. Performance assessment of cucumber segmentation.

Errors	Centroid: x-axis	Centroid: y-axis	Orientation
Mean Absolute Error	6 pixels	5 pixels	10.1°
Minimum Error	0 pixels	0 pixels	0.2°
Maximum Error	29 pixels	16 pixels	53.5°

truth images and the corresponding orientations of the blobs detected by the proposed algorithm. Orientation is defined as the angle between the x-axis and the major axis of the ellipse that has the same normalized central moments as the visible area of the considered cucumber.

After evaluating the results provided by the proposed algorithm with respect to the ground truth data, we found that the position errors measured for the considered centroids ranged from 0 pixels to 29 pixels in the x-axis and from 0 pixels to 16 pixels in the y-axis, with a mean absolute error of 6 pixels in the x-axis and 5 pixels in the y-axis. The absolute orientation error ranged from 0.2° to 53.5°, with a mean absolute error of 10.1° (see Table 4).

IV. DISCUSSION

The performance evaluation results at the pixel level show that the proposed detection algorithm exhibits a high hit rate of 91.79%, a low FPR of 2.56% and an acceptable FNR of 8.21%. A more detailed observation of Tables 1 and 2 reveals that the proposed algorithm increases the TPR and decreases both the FPR and the FNR relative to those of the SVM classifier described as an intermediate processing step in Section 2. This improvement is mainly achieved by the introduction of the Euclidean distance transform to eliminate less compact blobs and the introduction of the category classifier based on the bag-of-visual-words model, which provides better discrimination among the blobs that correspond to cucumbers, flowers and young leaves.

At the fruit level, the proportion of cucumbers detected by the proposed algorithm that are actual cucumbers is 90.10%, which indicates that only a small number of cucumbers are not detected. In analyzing the processed images, we observed that the occurrence of false negatives was due to two main reasons: (i) cucumbers suffered from severe occlusion, making each of their ends invisible, and (ii) cucumbers were overexposed to light. These two cases can be observed in the examples shown in Fig. 14. In addition, the average precision provided by the detection algorithm was 85.65%, which indicates a slightly higher presence of false positives compared with the number of false negatives. Common misclassification errors are produced by atypical leaves colorations, atypical clusters of flowers, and problems with separating cucumbers and stems. Nevertheless, compared to the results provided by the simplified, state-of-the-art wire cultivation systems described, the recall of 90.10% and the precision of 85.65% reflect considerable success for the stated application. Importantly, all previous results reported in the literature

(a)

(b)

FIGURE 14. Examples of undetected cucumbers. (a) A severely occluded cucumber and (b) a cucumber overexposed to light.

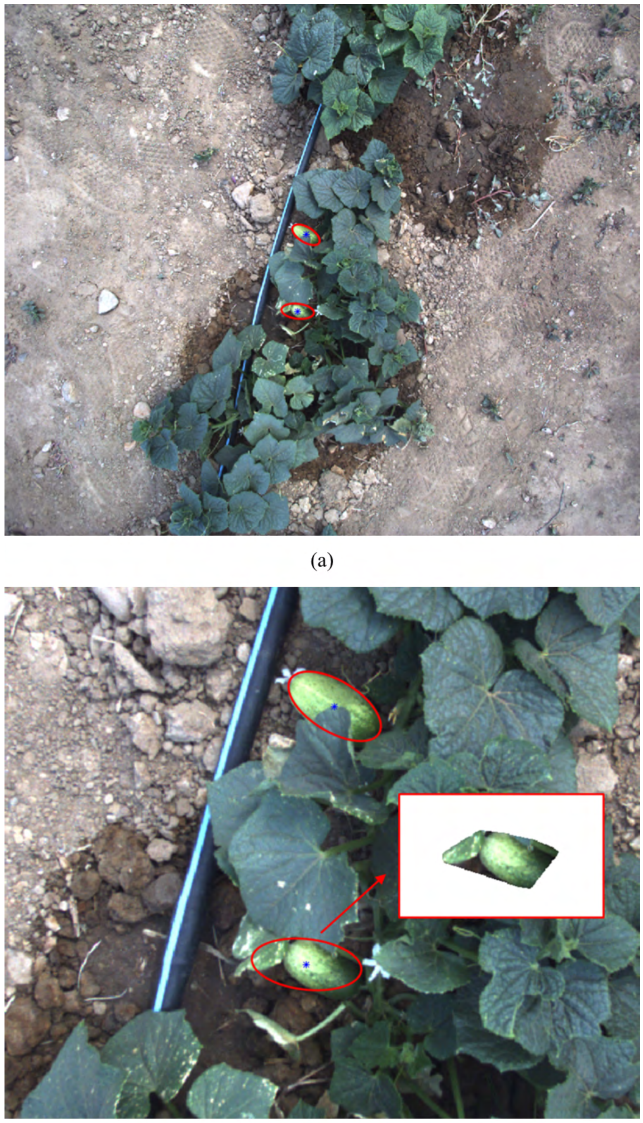
are related to cucumbers grown in greenhouses using wire cultivation systems. Most of the algorithms designed for wire cultivation systems are based on a series of assumptions that are not met in field-grown cucumber scenarios, such as the fact that cucumbers are always hanging vertically. Scenarios for wire cultivation systems are also less affected by occlusions and are therefore less prone to false positives and false negatives. To the best of our knowledge, the results presented here are the first reported for field-grown cucumbers in natural scenarios.

On the other hand, the F-score of 0.878 provided by the proposed algorithm proved to be quite competitive compared with other methods based on deep convolutional neural networks that have been proposed for detecting other fruits, such as the one presented in [10] with an F-score of 0.881 for the detection of mangoes, and the other described in [11] with an F-score of 0.838 for the detection of sweet peppers and rock melons. Therefore, this competitive F-score supports the use of the proposed algorithm for the detection of field-grown cucumbers, in contrast to other promising approaches based on deep-learning, which are heavier computationally and do not offer much difference in terms of accuracy.

Regarding the performance results related to cucumber segmentation, the mean centroid position errors obtained from the experimental results are 6 pixels on the x-axis and 5 pixels on the y-axis, which are quite acceptable considering that the resolution of the RGB camera is 2448 pixels $\times$ 2050 pixels. However, the mean absolute orientation error was 10.1°, although a maximum error of 53.5° was obtained in one of the processed scenes. Orientation is the variable most strongly affected by the detection errors at the pixel level. Shadows, as well as stems and leaves with similar coloration—which additionally are close to the detected cucumber—can vary the area of the detected blob and consequently introduce an error into the orientation estimation. In contrast, centroid position error is not as severely affected by these conditions. It is also important to comment that manual labeling of pixels for the generation of the ground truth data is not 100% exempt from errors. Therefore, labeling errors can also adversely affect the performance results. Fig. 15 shows an example of the aforementioned case, in which the orientation estimation of the cucumber at the bottom of the image is affected by the pixel-level errors due to the similar coloration of the leaf.

However, the results obtained from the performance assessment are quite satisfactory and highlight the potential of the proposed solution.

Importantly, the time required for the proposed algorithm to process an image, depends on the complexity of the scene and the hardware platform where it is running. A more complex scene contains more blobs and thus, requires longer processing time. However, to provide an idea of the total processing time, we estimated the mean time for each of the main steps of the algorithm. The experimental results provide a mean time of 185 ms for obtaining the normalized color transformations from the original RGB image, 650 ms for the SVM pixel-based classification, 95 ms for the morphological operations, 65 ms for the Euclidean distance transform, 50 ms for the image category classification of each blob provided by the bag-of-visual-words model, and 65 ms for the segmentation of each blob using the watershed transform and the minima imposition technique. These results were obtained by running the proposed algorithm in the MATLAB environment in a HP Z420 workstation with an Intel Xeon E5-1620 processor and 3.6-GHz clock speed. Therefore, the time cost can be reduced if the proposed algorithm is optimally coded and executed in a real-time operating system.



(a)

(b)

FIGURE 15. Example showing how errors at the pixel level affect correct estimation of the cucumber orientation. (a) Result provided by the proposed detection algorithm and (b) close-up view of the blob utilized for the orientation estimation.

For the critical steps of the proposed algorithm, both the training of the multiclass SVM classifier and features extraction for construction of the visual vocabulary for the bag-of-visual-word model were fundamental for achieving successful performance. To increase the accuracy of the SVM pixel classifier, data were normalized and color transformations were introduced to make the algorithm more robust to changing illumination conditions. Regarding the bag-of-visual-words model, special attention was directed toward the inclusion of visual words of all the elements that produce false positives (such as young leaves, flowers and irrigation tubes from the background) to reduce them in the final detection.

A crucial parameter for correct operation of the proposed algorithm was the size of the window for cropping the image around each blob serving as a potential cucumber candidate. These cropped images are the inputs for the image category classifier and should provide sufficient information for recognition. The minimum size of this window was selected such that the cropped image could contain a cucumber template of average size. Another key parameter was the area threshold defined to automatically apply the segmentation procedure to a blob categorized as cucumber. The minimum area size was also selected based on the average size of the cucumber templates.

V. CONCLUSIONS

This paper presents a field-grown cucumber detection algorithm intended to be used in an autonomous harvesting robotic system. The proposed algorithm includes an SVM machine pixel classifier that provides the initial regions of interest for further processing, a Euclidean distance transform for eliminating less compact blobs that usually correspond to flowers and young leaves, an image category classifier based on a bag-of-visual-words model that increases detection robustness, and a segmentation procedure based on the watershed transform and the minima imposition technique.

Field-grown cucumber detection imposes several challenges due to the similar coloration of the fruits and the leaves, stems and flowers; the large number of occlusions, which creates high variability in the apparent shape of the cucumbers; and the random positions and orientations in which fruits can be found. However, preliminary experimental results demonstrate the satisfactory performance of the proposed algorithm and highlight its potential benefits.

Future work will combine the results of the proposed algorithm with the 3D data provided by a range sensor (e.g., a Time-Of-Flight camera) to improve the estimation of the position of the centroids and the orientation of the detected blobs and to provide the spatial location of the detected cucumbers to the harvesting robot. We will also consider extension of the proposed algorithm to detect other cucumber cultivars. To that end, we will study the feasibility of using a sensor fusion approach that includes an SWIR camera. Water strongly absorbs light in SWIR wavelengths due to the overtones and fundamentals of the three vibration frequencies of H_2O, symmetric and asymmetric O-H stretching and O-H bending. Thus, the reflectance on SWIR images decreases with increasing water content, which could contribute to discriminating cucumbers from others plant elements. However, an SWIR camera is much more expensive than an RGB camera. Therefore, whether introduction of this sensor is beneficial from an economic perspective must be investigated since an increase in the cost of the sensory rig could limit its incorporation in a future harvesting robot. Additional experimental campaigns are also planned to acquire datasets from other cucumber cultivars (e.g., Liszt RZ, Karaoke RZ and Componist RZ cultivars). With these new datasets, we will also investigate the possibility of replacing the classic SVM approach in the proposed algorithm by deep convolutional neural networks not only to determine whether the algorithm can be extended for different cucumber cultivars but also to evaluate whether the efficiency of the proposed algorithm can be increased.

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