Computer Vision based System for Apple Detection in Crops

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Abstract: In recent times there has been an increasing need to improve apple production competitiveness. The automatic estimation of the crop yield or the automatic collection may contribute to this improvement. This article proposes a simple and efficient approach to automatically detect the apples present on a given set of images. We tested the proposed algorithm on several images taken on many different apple crops under natural lighting conditions. The proposed method has two main steps. First we implement a classification step in which each pixel is classified as part of an apple (positive pixel) or as part of the background (negative pixel). Then, a second step explore the morphology of the set of positive pixels, to detect the most likely configuration of circular structures. We compare the performance of methods such as: Support Vector Machine, k-Nearest Neighbor and a basic Decision Tree on the classification step. A database with 266 high resolution images was created and made publicly available. This database was manually labeled and we provide for each image, a label (positive or negative) for each pixel, plus the location of the center of each apple.

1 INTRODUCTION

Currently there is an increasing need to obtain higher quality products at a lesser cost, thus increasing competitiveness. Developing automatic systems to enable the use of human resources more efficiently in terms of precision, repeatability or time consumed is a good alternative. Also, estimating crops yield helps producers improve the quality of their fruit and reduce operation costs. Managers can use estimation results to plan the optimal capacity for packaging and storage (Robinson, 2006). As an example, the cost of harvesting citrus fully by hand may range from 25% to 33% of the total cost of production (Dougherty and Lotufo, 2003).

The overall objective of this article is to introduce an automated computer vision system for the detection and counting of red apples in trees. The present work is part of the design of a more complex system for the automatic estimation of crops yield and harvesting.

In order to detect pixels belonging to apples, three techniques are evaluated: Support Vector Machines (SVM), K-Nearest Neighbors (k-NN) and a very simple decision tree (DT). As an improvement to the outcome of pixel detection, morphology operations have been used. In order to detect the apples themselves, and given their shape, the Hough transform for circles has been used. Finally, a post-processing of the circles found is made, to rule out false positives detections.

2 RELATED WORK

There are several works on the detection of fruit using computer vision techniques.

There are two great approaches to the estimation of a crop yield, one is counting the apples and the other is doing the estimation through flower density. Several researchers have worked in the first category using color images (Linker et al., 2012),(Rakun et al., 2011),(Tabb et al., 2006), hyperspectral imaging (Safren et al., 2007), and thermal imaging (Stajnko et al., 2004). Aggelopoulou et al. (Aggelopoulou et al., 2011) worked on the second category, sampled images of trees in an apple orchard and found a correlation between flower density and crop yield. However, this method encounters a problem: the period between the flowering and the crop is too long and there are multiple unpredictable factors, such as weather conditions, which make the correlation exposed to variations from one year to the next.

Counting apples using computer vision puts forward several challenges, the most important of which being the variation of natural light, the occlusion of fruits due to foliage, branches and other fruits and the

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detection of one same apple in several images. Following are the techniques used by different authors to elude these challenges.

Wang et al. (Wang et al., 2013) present one way to avoid the variation of light by acquiring images at night with artificial illumination. The solution given by Jimenez et al. (Jiménez et al., 1999) to the occlusion is a post-processing of the images using Hough transforms with ellipses. Finally, for the challenge of multiple detections of the same apple in a sequence of images, Wang et al. (Wang et al., 2013) propose the use of a pair of stereo cameras to estimate the position of the apples and rule out those that coincide. A computer vision algorithm detects and registers apples that appear in sequential images and then counts them for the estimation. They had good results both in red and green apples and they make a full study of cases with results according to the type of cut of the trees, quantity of spots in the apples, accumulation of apples and occluded environments. Specifically, they carry out the identification of red apples by the following stages: through a hue threshold (H) and a saturation threshold (S), the pixels complying with the apples characteristics are detected and then, the apples are segmented individually using morphology operations. Finally, they look for the global position of the apple, thus avoiding to count it more than once. Gongal et al. (Gongal et al., 2016a) proposed a similar approach, were in addition to a pair of stereo images, a tunnel structure has build to minimize natural illumination effect which enable to reduced the variability in lighting condition. Images captured in a tall spindle orchard were processed. Zhao et al. (Zhao et al., 2005) present a method to identify apples using a single RGB image under natural illumination as input. To that end, they first define a redness measure as $r = 3R-(G+B)$, where R, G and B represent the red, green and blue values respectively of each pixel, then they apply morphological operations and finally an edge detection final step. Ji et al. (Ji et al., 2012) use the same kind of input RGB images as the previous work, and apply a median filter to eliminate the noise followed by a classification step in which they use SVM algorithm on a color plus shape space. Jimenez et al. (Jiménez et al., 1999) propose an automatic fruit recognition system and present a schematic review of the works developed until the end of the nineties. Their fruit detection methodology is able to recognize spherical fruits in natural conditions using a laser range finder which provide range/attenuation data of the sensed surfaces. Their recognition system uses a laser range finder model and a dual color/shape analysis algorithm to locate the fruits.

The work presented by Wang et al. (Wang et al., 2013) is likely the closest work to the present article. However, significant differences exist between this work and the present article. In first place Wang et al. propose a system that uses a two-camera stereo rig for image acquisition and works at nighttime with controlled artificial lighting to reduce the variance of natural illumination. While we work in ambient uncontrolled illumination conditions and use a single RGB camera. In addition, from the point of view of the numerical methods presented, we extend Wang et al. approach by including more advanced machine learning techniques and by facing apple detection problem in the context of an imbalanced problem (Barandela et al., 2003; Japkowicz and Stephen, 2002; Liu et al., 2009).

The main contributions of the present work are: (i) We improve previous approaches by the use of more robust machine learning techniques. In particular, by facing the pixels classification problem as a pattern recognition imbalanced problem. (ii) We present an updated review of the current state of the art. (iii) A database with 266 high resolution images was created and made publicly available (Marzoa, 2017a) .This database was manually labeled and we provide for each image, a label (positive or negative) for each pixel, plus the location of the center of each apple. To the best of our knowledge is the first publicly available database with such characteristics.

3 PROPOSED SOLUTION

This section describe the methods used to solve the problem posed. The methodology applied can be separated in three stages: construction of the database, classification of the pixels in apple or background and identification of the apples themselves.

3.1 Construction of the Database

The database is formed by 266 images acquired using natural light, at "Las Brujas - INIA" experimental station located in Canelones, Uruguay. Each image has an associated binary image where it is indicated, in white, whether the pixel belongs to an apple, or in black, if not. In its turn, there is a file per image with the coordinates of each apple's center. The data base is available for future works (Marzoa, 2017a).

3.2 Classification of Pixels in Apple or Background

To classify the apple pixels, a classic pattern recognition pipeline was followed. First a set of discriminative features is proposed to map the input RGB pixels to a more suitable feature space. Then, different classifiers are trained and evaluated.

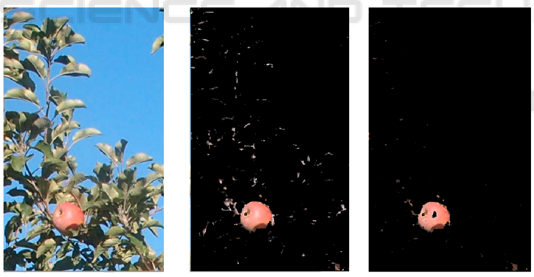
3.2.1 Feature Extraction

To describe those pixels that belong to an apple and those that belong to the background we use three basic features: Hue (H), Saturation (S), and a simple Texture descriptor.

Hue and Saturation. Apples have a reddish tonality which is different from almost all the other objects in a crop; therefore, tonality is a good differentiating characteristic.

In order to have robust representation of pixels under different illumination conditions, the input color space RGB is mapped into the HSV (Hue, Saturation, and Value) color space (Manjunath et al., 2001). The Hue and Saturation values are directly related to the color perceived of the pixels, while the Value is mainly related to the lightness of the scene.

The ranges of values of H with which better results are obtained were determined for each technique used. Tonality H is not defined for white, gray or black, that is why saturation, has to be used to exclude them. Figure 1(a) illustrates a test image of the database, Figure 1(b) show the result of segmenting the test image according to its values of H and Figure 1(c) show the result of segmenting using both H and S.



(a) Input image (b) After Hue segmentation (c) After Hue and Saturation segmentation

Figure 1: Example of segmenting a test image using different features.

Texture Descriptor. Another visible characteristic is that apples have less edges in their surface than grass, leaves or trunks. An edge may be seen as the place where the intensity of pixels changes dramatically (or noticeably), and this is obtained through partial derivatives. A large change in a gradient means a large change in the image. A method to detect edges in an image is then to place the pixels where the gradient is larger than the neighbors or, to generalize, where it is larger than a certain threshold.

In the present work, the Sobel operator (Szeliski, 2010) is used to estimate the gradient of the intensity for a given image. For each pixel, the operator gives the magnitude and the direction of the larger possible change.

Mathematically, two square $n \times n$ kernels are defined, G_x and G_y. Then, the continuous spatial derivatives are numerically approximated as,

$$\frac{\partial I}{\partial x} \approx G_x * I \text{ and } \frac{\partial I}{\partial y} \approx G_y * I \qquad (1)$$

where $*$ denotes the two dimensional convolution operation.

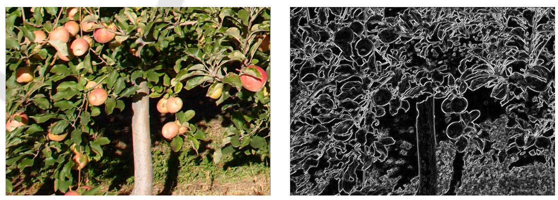
Kernels G_x and G_y are defined as,

$$G_x = \begin{pmatrix} 1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}, \quad G_y = \begin{pmatrix} 1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix} \qquad (2)$$

For each pixel of the image, an approximation of the gradient at the said point is estimated as,

$$|\nabla I| = \sqrt{\frac{\partial I}{\partial x}^2 + \frac{\partial I}{\partial y}^2} = \sqrt{(G_x * I)^2 + (G_y * I)^2}. \qquad (3)$$

Finally, edges can be defined as the set of pixels $\{x : |\nabla I(x)| > \tau\}$ for a given threshold τ. By representing the edges with pixels in white, in figure 2 the effect of applying Sobel filter to an image may be seen. Specifically, it may be observed how, while apples barely exhibit edges in their surface, leaves and the grass do.



(a) Input image (b) Edgedes after aplying Sobel

Figure 2: Example of image after apply Sobel.

Algorithm 1 summarizes the main steps of the feature representation step.

Notation. The features space defined for this problem is a three dimensional space where each pixel sample will be represented by a feature vector $\mathbf{x} = (h,s,td)^T \in \mathbf{R}^3$, h and s correspond to the features associated to the hue and saturation respectively, while td denotes the "texture descriptor" obtained from image's gradient. Those pixels label as belonging to an apple, will be refer as *positive* while pixels associated to the background will be refer as *negative*. Numerical label 1 and -1 will be associated to

Algorithm 1: Features of an image.

Input : RGB image $I : H \times W \times 3$ matrix
Output: 3D matrix $X : H \times W \times 3$ `// Hue, Saturation, and Texture Descriptor for each pixel.`

```
// Map RGB space to HSV space
```
$I_{HSV} = \texttt{rgb2hsv}(I)$
$X(:,:,1) = I_{HSV}(:,:,1)$
$X(:,:,2) = I_{HSV}(:,:,2)$
```
// Define Sobel kernels (2)
```
$(G_x, G_y) = \texttt{define\_sobel\_kernels()}$
```
// Convert RGB to a gray image
```
$I \leftarrow \texttt{rgb2gray}(I)$ `// Compute im. gradient modulus`
$I \leftarrow \sqrt{(I * G_x)^2 + (I * G_y)^2}$
```
// Local gradient descriptor
```
$X(:,:,3) = I$
return X

positive and negative classes respectively. A true positive/negative pixel will be a positive/negative pixel correctly classified, while a false positive/negative result will be a negative/positive sample misclassified.

3.2.2 Performance Measurement

Let us recall some well known performance measurements widely applied in the context of imbalanced problems (Di Martino et al., 2012; Di Martino et al., 2013b; Di Martino et al., 2013a; Kubat et al., 1997; Barandela et al., 2003; García et al., 2012). Given TP, TN, FP and FN as the number of true positive, true negative, false positive and false negative respectively, we define,

$$\text{Accuracy:} \quad \mathcal{A} = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$\text{Recall:} \quad \mathcal{R} = \frac{TP}{TP+FN} \tag{5}$$

$$\text{Precision:} \quad \mathcal{P} = \frac{TP}{TP+FP} \tag{6}$$

$$\text{F-measure:} \quad F_m = \frac{\mathcal{R}\mathcal{P}}{\mathcal{P}+\mathcal{R}} \tag{7}$$

Accuracy (or equivalently the error rate) is one of the most popular measures used to define optimality in pattern recognition problems. However in the context of highly imbalanced problems is not an adequate way of measuring and comparing different strategies performance. Let illustrate this point with a simple example. If just the 1% of the pixels of a set of images corresponds to pixels that belongs to an apple, we can design a trivial algorithm that classifies all the pixels as part of the background, i.e. the output label of this method is always -1. This approach will achieve an accuracy of 99% while non a single pixel nor a single apple will be detected. Precision and Recall are two important measures to evaluate the performance of a given classifier in an imbalance scenario. The Recall indicates the True Positive Rate, while the Precision indicates the Positive Predictive Value. It is clear that improving the recall will impact on the precision and vice-versa, so it is important to combine them in a single measurements, which is obtained by considering the F-measure.

3.2.3 Classifiers

Following is a description of the techniques evaluated for the classification of images pixels. We tested three different algorithms: a very simple decision tree, K-Nearest Neighbor and Support Vector Machine(Bishop, 2006). The first technique is extremely simple and efficient, and is likely the strategy that one must follow if the hardware resources are very limited. The other two methods are more advanced machine learning algorithms that for similar applications showed robust results in the past.

Decision Tree. A decision tree enables to classify a pattern in different classes. The tree nodes represent the questions of a certain property; the branches, the possible values of a property and each node leave represents one category. The pattern tested is allotted to the category attained. The links are mutually excluding and exhaustive. The main reasons to include such a simple technique are: firstly, to see how extremely simple strategies work in order to evaluate if the complexity of more sophisticated machine learning algorithms is justified. And secondly, to have very simple and efficient solution that can be embedded in robot prototypes with very limited hardware resources. With this ideas in mind, we propose the use of a simple tree structure with three nodes and four leafs, as it illustrated in Figure 3. This method has four free parameters that need to be tune: H_{min}, H_{max}, S_{min} and TD_{max}. To that end, a training dataset and an optimality criteria needs to be set. In the experimental section this aspects will be addressed.

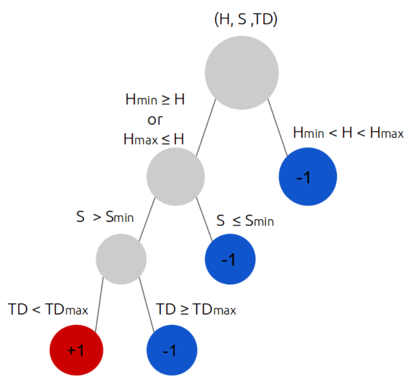


Figure 3: Scheme of the simple tree structure evaluated.

K-Nearest Neighbor (KNN). Once the features are defined and the data is mapped to this feature space, it is to be expected that pixels of the same class will be close with respect to each other on this domain. This is the basic idea behind the KNN technique. This technique consists of classifying the incoming point starting from its spacial location in the dominion of features, and to classify it in function of its nearest neighbors.

Choosing a right value of K is critical in KNN, since, if too small a K is taken, we would often encounter mistaken classifications for those pixels that are in the limit between two classes, while if a very large K is taken, the cost of looking into all the neighbors is too big and the class boundaries on the feature space may be blurred.

Support Vector Machine (SVM). Given a set of training examples where the data are marked as belonging to one class or the other, the training algorithm SVM builds a model to adjust each of the classes. By intuition, SVM constructs a model representing the training points in the space, separating the classes by the widest margin possible. When the new examples are put in correspondence with the said model, they are classified in one class or the other according to what side of the gap they are (Hearst et al., 1998).

These types of algorithms seek the hyperplane with the greatest distance, or margin, with the points nearest it itself. In this way, the points of the vector labeled with one category will be on one side of the hyperplane and the cases that are in the other category will be on the other side.

The representation through kernel functions (Scholkopf and Smola, 2001) offers a solution to the problems in which the classes are not linearly separable, by projecting the data into a space of greater dimension.

In this work a Gaussian radial basis kernel function (Scholkopf and Smola, 2001) is used,

$$k_\sigma(x_1,x_2) = e^{-\frac{\|x_1 - x_2\|^2}{2\sigma^2}} \tag{8}$$

This classifier has in total two free parameters that need to be set: σ which determines the shape of the kernel, and ν that set the compromise between the value of the margin and the amount of errors on SVM optimization (Hearst et al., 1998).

3.2.4 Implementation Details

The code is written in c++. To implement SVM, the functions given by OpenCV (OpenCV, 2017) are used. To implement KNN, the functions given by OpenCV to interface the FLANN (Muja and Lowe, 2009) library are used.

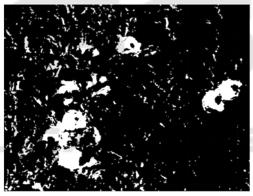
3.3 Counting of Apples

After having classified the pixels of an input image as part of an apple or the background, we have a groups of pixels labeled as apples, not their quantity or location. The next step was then to identify the apples within those groups of pixels. In order to do that, we resorted techniques applied to a binary image where the background is set as black and pixels that belong to an apple are set as white. The process we applied consists of the following three stages: (i) Pixels Mask Pre-processing, (ii) Detection of circles, and (iii) Circles Validation.

Pixels Mask Pre-processing. First applied morphological operations to remove the noise and to smoothen the regions edges. This helped to detect circles and rule out regions with a small area.

In the result of the recognition of apple pixels, there are regions with areas of diverse sizes, from regions of significant size to others that are nothing but a small set of noise pixels as seen in figure 4. The noise is generated by the foliage, branches and other elements that, due to their features resemble those of the apples, but that are actually isolated small regions that should be ruled out.

(a) Input image



(b) After clasification of pixels

Figure 4: Recognition of apple and background pixels before process the mask pre-processing.

The use of the morphological operations erosion and dilation is proposed. Erosion leads to the removal of the noise and the reduction of small regions, but it also leads to an increase in the gaps contained in the regions of significant size. On the other side, the dilation generates the opposite phenomenon, expansion of the regions and reduction of the gaps within them. For this reason four stages of morphological operations were applied, as seen in figure 5. At a first stage, the aim is to remove the noise without modifying the size of the area of the significant size regions and, at a later stage, the aim is to smoothen the edges and join the adjacent regions, keeping also approximately the original size of each area.

As structuring element, a circle is used, due to its proximity to the shape in which the apples appear in the images. The size of the circle must be set in order to remove the noise but taking care not to remove regions of interest. In the following section there is an evaluation of the more adequate size starting from the experiments results.

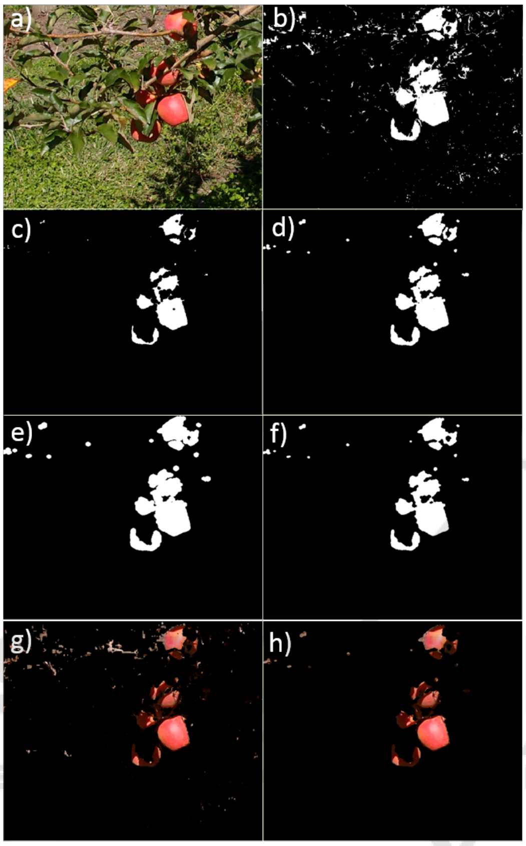


Figure 5: Stages of morphological operations (a) Original Image (b)Mask of pixel classification (c)Erosion (d) Dilatation (e) Dilatation (f) Erosion (g) RGB Mask of pixel classification (h) RGB Mask after applying morphological operations.

Detection of Circles. At a second stage, we recognize the circles present in the binary image which is the result of the recognition of the pixels. Since apples present a geometrical shape very near a sphere, in two dimensions images they will be seen as circles, whatever the location where the image is acquired.

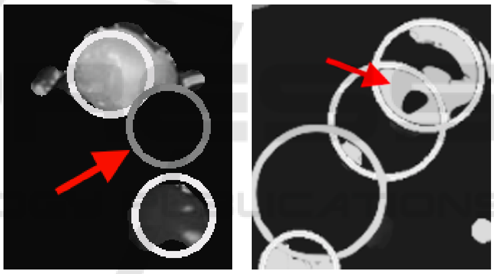
The Hough transform for circles (Brunelli, 2009) is used as method to recognize the circles present in the binary images obtained after the previous step.

Cicles Validation. The last stage, after having obtained a collection of circles with their radius and centers, consists of studying each one of them in order to validate which of the candidate circles actually represent an apple in the figure. Too occluded apples will generate small areas but not so much as to be ruled out by the morphological operations. If, moreover, they exhibit curved edges, a circle will be detected which, while belonging to an apple, does not represent that apples real location. Also, it may well be that, by being occluded, one same apple may generate more than one separated and curved area, thus resulting in only one apple being counted as several. Examples of the previous situations are illustrated in Figure 6.

(a) Input image (b) Mask after pixel classification

Figure 6: Example of how an apple may generate more than one separated area or a curved are.

Another possible situation may be seen in Figure 7(a). In this case a circle was detected because the higher region presents an outward circular curve, which leads to the detection of indicated circle. As a result, an empty circle is detected inside it.



(a) (b)

Figure 7: Wrong circles detected because the higher region presents an outward circular curve or because a region exhibits circular gaps inside.

To avoid detecting wrong circles, we suggest ruling out detected circles whose area is less than a minimum area. This means that, for each circle, the area of the region it includes is studied and the circle will be ruled out if the said area is less than a defined percentage of the total are of the circle.

The second stage within the post-processing of circles is to study the intersection of the circles.

As seen in figure 7(b), if a region exhibits circular gaps inside it is possible that more than a circle will be detected in it. To avoid these false detections, the area in each circle is studied and the region that intersects with other circles already studied is deducted.

In the case of figure 7(a), where first the higher circle is detected, we study the area of the second circle and deduct the intersection marked with the red arrow. In this case, the second circle will be ruled out, since the area is too small. If, on the contrary, the remaining area of the second circle is noticeable, it would not be ruled out but would be taken as a second apple.

Algorithm 2 summarizes the main steps performed for the detection of apples on the binary mask obtained after the pixel classification.

Algorithm 2: Apple detection.

```
Input  : Mask result of pixels classification
         M : H × W × 1
Output: List of centers and radiuses of the
         circles  circles_ok
// Morphological operations
M = erode(M) // Eliminates noise
M = dilate(M)
M = erode(M) // Smooths regions
M = dilate(M)
// Find circles
circles(1,:) = HoughCircles(M)
circles_ok = NULL
for each c in circles do
    // Discard circles whose area is
       less than a minimum area
    mask_c = new_image()
    mask_c =
      circle(mask_c, c.center, c.radius)
      mask = mask_c  &  M
      p = countNonZero(mask) *
      100/(c.radius^2 * π)
    if p > area_ok then
        // Study the region that
           intersects with other
           circles already studied
        intersected_circles =
          intersected_circles(c, circles_ok)
        if intersected_circles is NULL then
            circles_ok.add(c)
        else
            mask_intersec = mask_c
            for each c_int in
              intersected_circles do
                mask_intersec =
                  mask_intersec − c_int

            p =
              countNonZero(mask_intersec) *
              100/(c.radius^2 * π)
            if p > area_intersect_ok then
                circles_ok.add(c)
return circles_ok
```

4 TRAINING STEP

This section present the results obtained in the training step, considered according to each technique studied and their comparison. Cross validation with 10 iterations is used for all trainings.

4.1 Data Base

In classification works using computer vision, the database is an essential cornerstone; it is from this that the condition of effectiveness of the techniques studied are set. In this case the database is composed by images acquired in the outdoor, with natural light, seeking variety in them in order to be as close to reality as possible. The database created besides the images includes a labeling of which pixels belong to apples and which to background, as well as the coordinates of the center of each apple.

Since the database has 266 images, with an average resolution of 600x800, there is an approximate total of 63.840.000 pixels, which requires a memory structure of almost 64 million places, and this has to be multiplied by three, since the features being evaluated are three. It is then of utmost importance to carry out a study of the minimum percentage of pixels required that will be taken, so that it can be an acceptable representation of the total of the pixels in the database. In view of this, the percentage is changed and the pixels are classified (as apple or non apple) using the decision tree, given that this is the technique that requires less execution time. By increasing the quantity of pixels, after using 0.4% of the total of pixels, the measure of success used (f-measure) remains stationary.

4.2 Fitting for the Parameters of Apple Pixels Detection

Following is the fitting of the parameters for each technique.

Decision Tree. The valid values for the parameters studied are as follows: Hue in a range between 0 and 180, Saturation between 0 and 255 and edge density between 0 and 100.

The values that gave the best results for the decision tree were: $Min\_H = 13$, $Max\_H = 161$, $Min\_S = 47$ and $max\_edges = 76$.

K Nearest Neighbor. Due to the features of the KNN method when in a problem of imbalanced classes, it is necessary to limit the percentage for the training of the biggest class. In its turn, the quantity of nearest neighbors considered, K, should be determined.

Support Vector Machine. The study of effectiveness and efficiency was made by varying parameters gamma and C of the kernel, gamma being the weight of each points influence while C exchanges wrong classification against surface simplicity. The values that returned best results being $C = 100$ and $gamma = 1$.

Comparison of Techniques. Comparing the results obtained by using the three techniques, we have that KNN is the technique that yields the best results, as seen in figure 8. Also, it shows the improvement between using only one characteristic and using three.

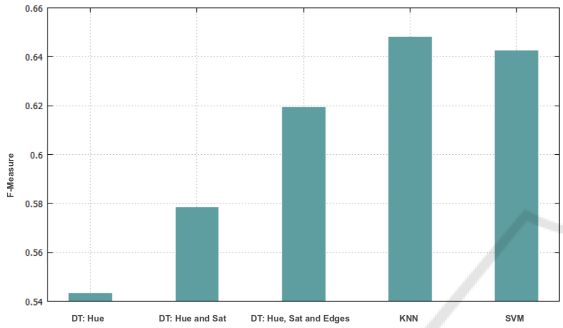


Figure 8: F-measure average obtained in the recognition of apple pixels. First it shows the improvement of using three characteristics with tree decision and then the comparison using KNN and SVM.

Since the three techniques used the same dominion of characteristics for their classification, it is interesting to compare the classification of each of the methods for a set of points normalized from 0 to 1 (a cube) of the three characteristics; they may be seen in 3D, as shown in figure 9.

It is observed how, while the cloud of apple pixels is similar in the three methods, KNN and SVM do not present straight borders, which is closer to reality.

Morphology. The study of the morphology parameters was made using the Decision Tree technique because is more quickly that the others. The parameters used for the technique are who gives better results of f-measure. It was used cross validation, using values between 1 and 10 for the radios, obtaining the bests results when use radio of 5px for erode and 7px for dilation.

4.3 Fitting for the Parameters of Apples Detection

Following is the fitting of parameters for the detection of the apples in themselves. First there is a description of the parameters used to detect the Hough circles and then of the parameters used for the post-processing.

Detection of Hough Circles. The minimum distance between circles detected and the accumulator threshold was varied. The minimum and maximum radium was determined by estimating the average radius in the database: the values were 20 and 75 pixels, respectively.

In order to find out whether the circle found is the same one labeled at the database only by using their centers, in most cases they would be found not to coincide, so a margin of tolerance between centers equal to the value of the radius of the circle found is used.

The Hough transform uses two values to be determined: the minimum acceptable distance among circles and an accumulator that indicates the percentage that should coincide in the image with the circle found. The values obtained for the detection of circles that gives better, with an average distance among circles of 67 and an accumulator of 8.

Post-processing in Circles. Using 20% of the area of an apple as minimum area for a circle to be considered valid, better results are obtained by giving an average FV of $0,53 \pm 0,04$.

In the table 1 it shows the values of all the parameters used in the project.

5 RESULTS

The proposed approach for automatic apple detection consists on two main steps as was described in the previous Sections. Firstly, the individual pixels of each input image are classified as *Positive* or *Negative* (recall that the positive class is associated to pixels that potentially belong to an apple). Secondly, the morphology of the set of Positive pixels is analyzed to find circular structures that lead to the final goal of detecting the apples present in the target image. It is clear that the individual performance of both stages will impact on the overall performance of the proposed approach, and so both steps need to be carefully analyzed and trained as explained in the previous Section.

Let us start by analyzing the results obtained for the classification of the individual pixels. Figure 8 summarizes the results obtained for different classification methods over the test dataset and Figure 9 illustrates how the feature space is partitioned for the classification strategies evaluated. The performance of different methods is evaluated according to the F-measure obtained due to the imbalance nature of this problem (as explained in Section 3.2.2). The most accurate algorithm in terms of the F-measure was the K Nearest Neighbor method with approximately 64% of F-measure respectively. In terms of efficiency, the

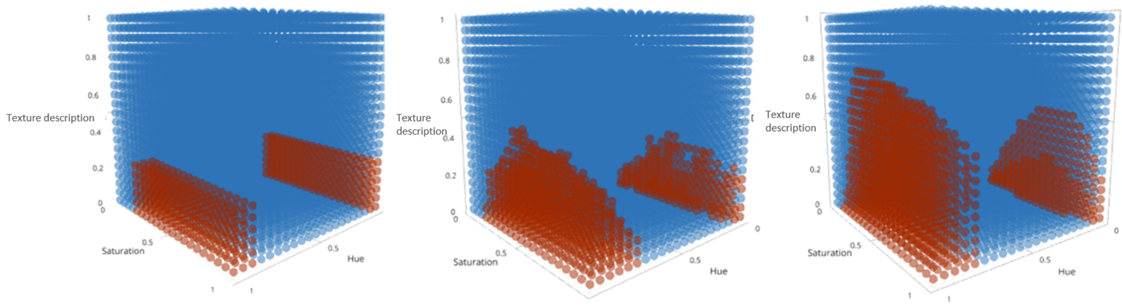


Figure 9: Classification of each of the methods for a set of points normalized from 0 to 1 of the 3 characteristics. First is the decision Tree, then KNN and finally SVM.

simple decision Tree achieved an overall F-measure of 62%. Depending on each particular application, the limitation on the hardware and computational resources, and the requirements on the performance detection, one need to choose the method that better fits the problem characteristics.

Figure 10: Examples of apples detected. Video and additional material at (Marzoa, 2017b).

Using the mask of pixels classified by decision tree method, morphological operations are applied to achieve the final goal of detecting the apples present in the test images. Again, part of the images of the data set were used to train and fit the parameters of the solution implemented, while other independent images (never used during the training step) are used for testing the proposed solution. Figure 10 shows the output of the proposed solution for four input test images. As in the pixel classification step, the final performance of the proposed solution is analyzed in therms of the F-measure. It is important to point out that while the definition of F-measure, Recall and Precision is unique, the meaning of this quantities is different in this second step. In the pixel classification step, we define the TP (true positive) quantity as the number of pixels classified as part of an apple that truly belong to an apple, in the final step, TP is defined as the number of apples correctly detected, while FP is the number of apples detected that are not present in the image (false detections) and FN corresponds to the number of apples present in the image that where not detected by the method. Table 2 summarizes the final results obtained for the detection of apples. In this table, the Recall represents the percentage of apples present in the input image that are correctly detected, and the Precision indicates the percentage of detections give by the algorithm that actually correspond to an apple. As explained in previous Sections, Recall and Precision are combined in a single measure: the F-measure. Others works dont use the same measurements that us, in general, the focus is on the over all apple count so we had to calculate the results that are presented in this table using the images and results presented in theirs articles.

To conclude this Section is important to highlight some difficulties that arises when comparing different apple detection approaches. In first place, different solutions proposed in the literature make use of significantly different setups. For example: some works make uses of stereo pairs of cameras plus high precision positioning systems (Wang et al., 2013), tunnel like structures (Gongal et al., 2016b) to control illumination conditions, hyperspectral cameras (Safren et al., 2007), or thermal imaging devices (Stajnko et al., 2004). Secondly, the conditions of crop yield also has a great impact on systems performance, for instance, special fruit thinning may significantly simplify the problem. Thirdly, the success measurements uses also present significant variations, for example, in (Wang et al., 2013) the focus is on the over all apple count, hence false positive detections may be compensated with false negative detections (while the f-measure penalize both).

6 CONCLUSIONS

This article presents a simple pipeline for the detection of apples in crops using pattern recognition and computer vision tools. The set up consists of a single RGB camera that captures under unconstrai-

Table 1: Values of parameters used.

Algorithm	Parameter	Value
Decision tree	Hue min Hue max Sat min Edges density	13 161 47 0 - 100
KNN	K % of pixel background	23 45%
SVM	*Gamma* C	1 100
Morphology	Erode Dilate	5 7
Hough circles	Min radio Max radio Min distance Accumulator	20 75 67 8
Post-processing in circles	Min area	20%

Table 2: Recall, Precision and F-measure for different apple detection strategies.

Method	Recall	Precision	F-measure
(Zhao et al., 2005)	67,9%	100,0%	80.1%
(Linker et al., 2012)	72,8%	97,2%	83.3%
(Ji et al., 2012)	46,4%	100,0%	63,4%
ours	92,0%	90,3%	91.5%

ned natural illumination conditions in unthinned apple crops.

The detection of apples was made in two big stages. First the classification of pixels and then the detection of apples within the previously classified pixels. Three techniques were studied for the classification of pixels: decision tree, KNN and SVM. The best results were obtained with KNN algorithm, while the decision tree probes to be a very adequate alternative if computational cost or time are very limited. The determinant features to make the classification were tonality, saturation and edge density. As an improvement of the recognition of pixels, morphological operations were used. Once the pixels had been classified, we proceeded to the detection of the apples by using the Hough transform for circles. Finally, the quantity of pixels within the circles found was analyzed to validate the circles detected and significantly reduce the number of false positive.

The main contributions of this work are: The use of robust machine learning techniques by facing the problem as a pattern recognition imbalanced problem. We present an updated review of the current state of the art and create a database with 266 high resolution images which was made publicly available.

There are some evident path in which this work can be pushed forward. For example: the output of multiple classifiers can be combined to improve the over all performance (Kuncheva, 2004). With the increase of the number of publicly available databases, the design of complex modern classifiers such as deep neural networks will be possible. And finally, instead of processing individual images, sequence of images (video data) can be analyzed ensemble exploiting the temporal correlation of the data.

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