ABSTRACT

Trunk diameter is a variable of agricultural interest, used mainly in the prediction of fruit trees production. It is correlated with leaf area and biomass of trees, and consequently gives a good estimate of potential production of the plants. This work presents a low cost, high precision method for autonomous measurement of trunk diameter of fruit trees based on Computer Vision. Autonomous methods based on Computer Vision or other techniques are introduced in the literature for they present important simplifications in the measurement process, requiring little to none human decision making. This presents different advantages for crop management: the method is amenable to be operated by unknowledgeable personnel, with lower operational costs; it results in lower stress levels to knowledgeable personnel, avoiding the deterioration of the measurement quality over time; or it makes the measurement process amenable to be embedded in larger autonomous systems, allowing more measurement to be taken with equivalent costs. In a more personal aspect, the present work is also a successful proof-of-concept for our laboratories and regional research institutions in favor of autonomous measurements based on Computer Vision, opening the door to further investigations in other important agronomic variables measurable by Computer Vision. To date, all existing autonomous methods are either of low precision, or have a prohibitive cost for massive agricultural adoption, leaving the manual Vernier caliper or tape measure as the only choice in most situations. In this work we present an autonomous solution that is costly effective for mass adoption, and its precision is competitive (with slight improvements) over the caliper method.

RESUMEN

El diámetro del tronco es una variable de interés agrícola utilizada principalmente en la estimación de la producción de árboles frutales. Se correlaciona con el área foliar y la biomasa de los árboles, y por lo tanto da una buena estimación del potencial productivo de las plantas. En este trabajo se presenta un método de bajo costo y alta precisión para la medición autónoma de diámetro de tronco de árboles frutales basado en técnicas de Visión Computacional. Se presentan algunos métodos autónomos existentes en la literatura, basados en Visión Computacional y otras técnicas, que logran simplificaciones importantes en el proceso de medición, requiriendo poca o ninguna intervención humana. La automatización presenta diferentes ventajas para el manejo del cultivo: es susceptible de ser utilizado por personal con poco o nulo conocimiento, llevando a costos operativos más bajos; requiere un menor nivel de estrés a personal con conocimientos, evitando el deterioro de la calidad de la medición a lo largo del tiempo; y hace que el proceso de medición sea susceptible de ser embebido en sistemas autónomos no tripulados, lo que permitiría realizar más mediciones con costos equivalentes. En un aspecto más personal, el presente trabajo resulta una prueba de concepto exitosa para nuestros laboratorios e instituciones de investigación regional en favor de mediciones autónomas, basadas en Visión Computacional, abriendo la puerta a nuevas investigaciones para otras variables agronómicas importantes, susceptibles de ser medidas mediante técnicas de Visión Computacional. Hasta la fecha, todos los métodos autónomos existentes son de baja precisión o tienen un costo prohibitivo para la adopción masiva en agricultura, dejando el calibre
INTRODUCTION

The main contribution of this work consists in a low cost, high precision and autonomous measuring method of trunk diameter based on techniques for Image Segmentation of Computer Vision. Trunk diameter is a variable of agricultural interest in the production of fruit trees. The trunk of a plant complies with the vital function of transporting water and nutrients from roots to consumption areas (shoots, leaves, fruits), as well as with the accumulation of reserve substances (32). It is correlated with the capacity of the plant to sustain growth and maturation of shoots, leaves and fruits, and it is a good estimator of other indicators of the plant productive potential, such as biomass and leaf area (11, 12, 39). There are numerous allometric relationships reported estimating leaf area and biomass of different trees using mainly the cross-sectional diameter or area of the trunk (3, 10, 17, 24, 30, 40, 52). Therefore, obtaining accurate measurements of trunk diameter helps obtaining better estimates of variables such as leaf area and biomass, and consequently better estimation of potential production of the plants and the plants status evolution.

Table 1. Potential errors that can occur in the measurement process based on caliper.

<table>
<thead>
<tr>
<th>ID</th>
<th>Error description</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Reading of the measuring instrument.</td>
</tr>
<tr>
<td>II</td>
<td>Transcribing values into the datasheet.</td>
</tr>
<tr>
<td>III</td>
<td>Writing values in the slot corresponding to its plant ID.</td>
</tr>
<tr>
<td>IV</td>
<td>Transcribing the datasheet into the computer.</td>
</tr>
<tr>
<td>V</td>
<td>Interpolation errors</td>
</tr>
</tbody>
</table>

In practice, the trunk diameter is measured using manual methods such as Vernier calipers or measuring tapes. Although these instruments can be considered high precision (0.05mm in the case of a standard caliper and 0.5mm in the case of a standard tape), they may result in important measurement errors. On one hand there are the human errors that may occur during extensive measurement campaigns due to fatigue, haste or carelessness (errors I through IV in Table 1). Other errors may arise indirectly due to the elevated costs in labor stipends of the manual method that force agronomists to save in the number of trees for which measurements are performed. In practice, this may be mitigated using interpolation methods such as Krigging (16), but in practice even the minimal number of measurements required by these methods for accurate estimates may be prohibitive. We refer to this as interpolation errors and list it together with the other errors in Table 1. Without precise information of agronomic variables such as trunk diameter, agronomists may lack information required for selective harvesting (8), or proper and assertive decisions over crop management such as amount of watering, fertilizers and pruning (15); resulting not only in poor harvest predictions but in an unnecessary stress of the plant that may affect the fruit quality, production or even the life of plant.

Different autonomous measurement methods have been introduced in the literature with the hope of mitigating these errors. Mostly, their intent is not so much in increasing the precision of individual measurements, as manual methods already present sufficient precision, but more on mitigating the effect of manual or interpolation errors due to human fatigue or elevated costs of human labor. An autonomous system reduces to a minimum the required human intervention during the measurement process. Our method, although not entirely autonomous as it requires taking a
photograph and fixing a quick clamp manually, it requires little to none knowledgeable decision making, which makes it possible to be operated by unknowledgeable, and thus lower stipend or more available personnel. Also, it opens the possibility of further automation by embedding the system within a mobile system that autonomously measures large number of trees (e.g., unmanned land or air vehicles). Such a system would allow massive measurements of the entire population of trees, with the consequent benefits in crop management operations. This is the goal of Precision Agriculture (PA) that has been the response of the scientific and industrial community for mitigating the impact of interpolation errors. As a whole, the PA is a group of technologies that increase the spatial resolution of crop management by providing the means to reduce the costs of measurements and interventions, thus increasing the spatial density of the treatments. Among its technologies we can list autonomous sensors embedded in wireless ad-hoc sensor networks, GPS systems for global positioning, geographical information systems for proper management of the sensed data, autonomous systems for differential management of the inputs, and other technologies of information and computation (6). Recent years has shown an important increase in the adoption of these technologies both in production and academic settings. Examples for wheat, soy, potato, corn, beet, barley, sorghum, cotton, oats, and rice can be found in (6), together with important advances in the commercial application of PA for the production of vineyards (2, 7), citric trees (45), banana trees, tea, date palm trees, and even management of sport fields (5) and train systems (1). In parallel, several Universities and research groups around the world raised their academic interest in PA as exemplified by the International Conference on Precision Agriculture being held continuously since 1990, together with the European Conference on Precision Agriculture that has been held in nine occasions since 1996. In addition, many aspects and contributions of PA have been discussed regularly in general agricultural meetings and journals.

![Figure 1](image1.png)

**Figure 1.** (a) Original image of a grape vine. (b) Segmentation into four regions: grape (black), trunk (dark grey), foliage (light grey), and the rest of the scene named *background* (white).

**Figura 1.** (a) Imagen original de una vid. (b) Segmentación en 4 regiones: uva (negro), tronco (gris oscuro), follaje (gris claro), y el resto de la escena llamado *background* (blanco).

The advantages and benefits provided by the PA are sustained mainly by the technologies of autonomous sensing. The market presents autonomous sensors for a great diversity of magnitudes such as temperature, humidity (air and soil), luminosity, solar radiation both visible and ultraviolet spectrum, different gases, atmospheric pressure, NDVI, and more. However, some magnitudes are too complex for existing electronic sensors that still require human visual inspection. Such is the case of trunk diameter, fruit grain diameter, leaf area, bud count, fruit localization within trees, defects in fruit surface, weed localization, optimal harvesting time, among others. All these (and other) variables are strongly correlated with quality and productive potential of the crop but are currently mostly...
produced by a fluorescent lamp, with four cylindrical poles of different diameters used as controlled experiments were conducted in a controlled laboratory environment under ambient light condition. This information is not reported however.

Our contribution takes advantage of Image Processing and Image Segmentation techniques, which are supported by advances in fundamental algorithms of Computer Vision such as Markov Random Fields, Conditional Random Fields, Edge Detection, Clustering, Fuzzy Sets, Thresholding, Texture analysis, Deformable Models, among others (4, 48). Image Processing is the use of computer methods for preprocessing a digital image and converts it into a form suitable for further analysis (48). The term Image Segmentation refers to the process of partitioning a digital image into a set of regions, each of which is strongly correlated with some object of the real world, or background. The pixels of each region are grouped based on some uniformity criteria (see Appendix A). For instance, Figure 1-a shows the original image of a grape vine and Figure 1-b its segmentation into four regions: grape (black), trunk (dark grey), foliage (light grey), and the rest of the scene named background (white).

### Previous works

Several works of autonomous measurement of trunk diameter has been presented previously in the literature. For instance, Tetuko et al (50) propose a method for estimating ranges of values of trunk diameters over large areas of dense forests of four species of Java-Indonesian trees. Their approach project L-band microwaves on the trunks, and uses a Synthetic Aperture Radar (SAR) to read the resulting backscattering coefficient, later correlated with trunk diameter. In their paper they use a SAR mounted on the JERS-1 satellite, which has a resolution of $18\text{mt}$ per pixel, although other existing SARs may range from $200\text{mt}$ per pixel (low resolution) to $1\text{mt}$ per pixel (high resolution). Technologies known as airborne SAR sensors (mounted on airplanes or other atmospheric aircrafts) achieve resolutions of $10\text{cm}$ to $30\text{cm}$ per pixel, but require specialized and expensive equipment. Satellite SARs, in contrast, require access to a satellite, with lower cost and higher availability than the airborne version, but still prohibitive or inaccessible to most producers. In either case, however, the resolutions are still large enough to prevent their use in any practical PA application. Jutila et al (22) presents a method designed for forest harvesters. Their method consists in a 2D laser range finder (of SICK Sensor Intelligence company) mounted on an all-terrain vehicle, used to obtain depth information. Their method achieves good precision in pines forests with an error mean of $0.6\text{cm}$ and standard deviation of $2.2\text{cm}$. One limitation for adoption of this technique in fruit trees production is the high cost of equipment needed for implementation. In Omasa et al (41), a 3D model of a city park was used in order to quantify the biophysical variables of trees, such as height, canopy diameter and trunk diameter. The 3D model was generated with a scanning Light Detection and Ranging (LIDAR) technology, combining data from airborne sensors with data on-ground using portable sensors. The authors reported errors less than $0.3\text{cm}$ in the three trees that were measured. While this method shows high precision, the high cost of aerial and portable LIDAR sensors makes it privative for most fruit trees producers. Kan et al (23) presented a method based on Computer Vision for measuring trunk and branch diameters from images acquired by a conventional digital camera. A calibration stick is included in the scene next to the tree trunk, and it is detected using template matching (9). The trunks and branches of the tree are also detected by template matching and then the number of trunk and branch pixels is counted. The actual diameters are obtained by multiplying the trunk and branch diameters in pixels by the size of a pixel obtained through the calibration stick. This method was tested on 50 images resulting in a mean error of $0.67\text{cm}$ and standard deviation of $1.73\text{cm}$. However, when the background of the images is complex (for instance, not a clear sky), the calibration stick may not be detected and the method fails to obtain the diameters. The results over the 50 images show a success rate of 90% in detecting the calibration stick. For a definite assessment of their approach one would require information on the proportion of these images with complex backgrounds. This information is not reported however. Thamrim et al (51) discussed a new and relatively simple tree diameter measurement technique using a high-performance, non-intrusive infrared sensor. The experiments were conducted in a controlled laboratory environment under ambient light condition produced by a fluorescent lamp, with four cylindrical poles of different diameters used as controlled
replacements for trees. About 80% of the experiments show errors of less than 0.2 cm for each pole, with an average of 0.2 cm for standard deviations. The rest of the results give errors between 4 cm to 5 cm as a consequence of the extra complexity of their problem caused the sensor mounted on a moving vehicle. Although these results are promising, they still present 20% of cases with unacceptable errors on a controlled environment.

**Our Contribution**

All the above techniques have significantly contributed in the process of obtaining a high precision, low cost autonomous measurement technique of fruit trees trunk diameter. However, these solutions are not optimal: some are low cost but low precision (or equivalently high failing rate), and others are high precision but high cost. In this paper we propose a low cost, high precision method based on Computer Vision for autonomous measurement of trunk diameter of fruit trees, whose cost is in the order of Kan’s technique (the lowest of all) and whose precision is in the order of Omasa’s (the highest of all). Equivalently, our approach presents precision equivalent to a Vernier caliper with a larger but still accessible cost (the digital camera, a PC and the quick clamp whose value ranges in the 30 US dollars), while maintaining the advantage of automation.

Our method consists in digitally processing images of a quick clamp (see Figure 2-a) gripped to the trunk (see Figure 2-b), obtained with standard commercial digital camera on realistic conditions of climate and luminosity. The images are computationally processed using the Computer Vision technique called **image segmentation** that discriminates the pixels of the clamp from the rest of the image, as illustrated in Figure 2-c. The measurement is completed by first measuring the horizontal distance in pixels between the internal edges of the clamps, and converted to centimeters multiplying this distance to the distance in centimeters of a pixel; obtained from the previously known height of the clamps in centimeters and its measure in pixels. In addition to a known height, the clamp also serves the purpose of determining the preferred location of the trunk diameter measurement. These stages of the method are presented in more detail in the following section. In personal conversations with agronomists, they considered our approach extremely simple, even simpler than measuring using a Vernier caliper. However, we present no proof in favor of this argument, leaving it for personal consideration of the reader.

![Figure 2.](image) (a) Quick clamp. (b) Original Image with the quick clamp. (c) Results obtained by the GMM segmentation algorithm for the original image and calculating the distance in pixels between the spade pads (points A-B) and height in pixels of a spade pad (C-D points).

The viability of this approach was assessed by comparing its results with the manual method based on caliper. The results show that the autonomous approach obtains a mean absolute error of 1.05 mm and a standard deviation of 0.95 mm, resulting trunk diameter values equivalent (slightly better) than to those of the manual method (see Table 2). In addition, our method presents two clear advantages over the manual method: avoids errors I, II, and IV (see Table 2); and eliminates the operator qualifications as an influencing factor, i.e., requires people with little or null knowledge and experience in agronomic experiments.
MATERIALS AND METHODS

This section describes the implementation details of our autonomous image-based method, as well as details on the experimental setups used for evaluation.

A. Implementation of Autonomous Image-based Method (AIM)

Trunk diameter measurements using image processing presents several difficulties. First, the trunk must be segmented out from the other elements of the scene such as soil, leaves, fruits, sky, and other plants. Second, the direction of the measurement must be detected. Third, the preferred measurement position along the trunk must be detected. Fourth, it is necessary to measure the distance in pixels between the edges of the trunk in the direction of measurement just determined. And conclude by re-scaling the measurement from pixels to millimeters.

In this work we incorporate the use of a modified quick clamp (shown in Figure 2-a) to address all these difficulties. The segmentation problem is simplified by changing the color of the spade pads of the grip to red as illustrated in Figure 2-b, a color rarely encountered in vineyards. With this modification it is possible to use simple color segmentation techniques for a successful and precise segmentation of the spade pads. With the spade pads segmented as illustrated in Figure 2-c, all remaining difficulties are easily addressed. The vertical of the pads is used as the direction of measurement, the position of the clamp along the trunk determines the preferred position for measurement, and the distance between their internal edges (points A and B in Figure 2-c) matches exactly the trunk diameter. Finally, the known height of the spade pads in millimeters \(|C-D|_{mm}\) and in pixels \(|C-D|_{pixels}\) obtained for the segment CD in the Figure 2-c, serves as a re-scaling ratio for converting the diameter \(|A-B|_{pixels}\) in pixels to the diameter \(|A-B|_{mm}\) in millimeters as follows:

\[
|A - B|_{mm} = \frac{|C - D|_{mm}}{|C - D|_{pixels}} |A - B|_{pixels} \quad (1)
\]

In practice, however, possible segmentation errors were averaged out by measuring several points \(A_n\) and \(B_n\) to obtain the reported diameter value:

\[
|A - B|_{pixels} = \frac{1}{N} \sum_{n=1}^{N} |A_n - B_n| \quad (2)
\]

With this setting, the measurement process requires the personnel to fix the clamp in the trunk, take the picture, and run it through our algorithm.

The spade pads segmentation technique consists in two stages: training and classification. The training stage uses manually segmented images to estimate a probabilistic model from color and segment information of pixels to later, during the classification stage, use the model to segment images autonomously by deciding the most probable segment of each pixel, given its color. Let us first introduce the details of the probabilistic model class we used: Gaussian Mixture Models (GMM) (4, 53), to later explain in detail the training and classification stages. GMMs are a weighted sum of Gaussian distributions that provide a multi-modal class of multi-variate density models. Figure 3-a shows an example for three Gaussians, colored red, green and blue; where each one has been already re-scaled by its weight. The figure also shows in black the resulting GMM. These models have two important advantages that make them particularly convenient for color image segmentation, as exemplified by the works (4), (18), and (48). On one hand, they have strong representational power, that by using a sufficient number of Gaussians, and by adjusting their means and covariances as well as the weights in the sum, almost any density can be approximated to arbitrary accuracy (4). On other hand, there are well-known, computationally efficient techniques for parameters estimation. In this work we used for parameter estimation the elegant and powerful method of maximum likelihood executed with the Expectation-Maximization algorithm (36). The works in (4, 18) explain in detail how to combine maximum likelihood in the algorithm Expectation-Maximization algorithm for estimating the numerical parameters of the GMM (i.e., means, covariance matrixes, and weights).
Training stage. During the training stage, a set of manually segmented images are used to estimate a GMM distribution used to model the probability that a pixel belongs to certain segment or object in the image (e.g., foliage, trunk, fruit). This stage is conducted during the design of the algorithm using images that are representative of the realistic conditions that may occur later during the measurement stage. In this work we used the well mixed set of cloudy and sunny images shown in Figure 4. For training, these figures have been manually segmented into two segments: spade pads and background, as exemplified in Figure 5. The set of all pixels of all 8 images were separated into two datasets, one per segment; with each datapoint containing the color information of the pixel. Image color is commonly coded according to the RGB color-space, i.e., the color of each pixel is represented by 3 components: red (R), green (G), and blue (B). For instance, in Figure 5 we show two pixels $\alpha$ and $\beta$, one for each segment. The RGB color code for these pixels is $\alpha=$ (245, 75, 48) and $\beta=$ (71, 126, 76). Experience from previous works (45) show that segmentation can be improved when the images are converted to the LUV color-space ($L$=luminance, $U$=saturation, $V$=hue angle), and
the luminosity component discarded, i.e., using only the saturation and hue angle components (13, 20, 48). Our datapoints, and therefore the resulting GMMs are 2D. For instance, converted to UV our two example datapoints become \( \alpha = (135, 38) \) and \( \beta = (-26, 31) \). We provide more details on color spaces in Appendix B. The two datasets (one per segment) consists therefore on the U and V values of each pixel corresponding to the segment of the dataset. Figure 6 illustrates this information as two, 2D scatter plots over the UV space, one for the pixels in the background (right), and one for the pixels of the spade pads (left). In addition, two histograms are shown for each plot, one for the U component (on the top horizontal side) and one for the V component (on the right vertical side). These histograms show empirically the multimodal nature of the background, and the unimodal nature of the spade pads. This justifies using a two modes GMM for modeling the spade pads color information, and at least a three modes GMM for modeling the background color information.

**Figure 5.** Left, original training image. Right, manually segmented image.

**Figura 5.** Derecha, imagen de entrenamiento original. Izquierda, imagen segmentada manualmente.

**Figure 6.** Scatter plot in the UV color-space for spade pads pixels (left) and the background pixels (right) of the image in Figure 2-d, together with the normalized histograms for U (top) and V (left) of each graph.

**Figura 6.** Diagrama de dispersión en el espacio de color UV para los píxeles de los tacos de la pinza (izquierda) y los píxeles del background (derecha) de la imagen de la Figura 2-d, junto a los histogramas normalizados de U (arriba) y V (izquierda) de cada gráfico.

We summarize the training stage as follows:

1. Take several pictures with the quick clamp attached to the trunk as shown in Figure 2-b on varying realistic conditions of climate and luminosity.
2. Convert all pictures to the LUV color space and discard the L component.
3. Using software for image editing, label all pixels in each image that correspond to the spade pads and background (for instance, coloring them red and green, respectively, as exemplified in Figure 5), and separate them into two datasets.

4. Using the training dataset of each segment, estimate the maximum likelihood numerical parameters of its corresponding GMM using the expectation-maximization algorithm.

**Classification stage.** During the measurement campaign, new images are autonomously segmented using the GMM models estimated previously during the training stage. This occurs in what is commonly called the classification stage, a stage that discriminates each pixel as part of the spade pads or as part of background. The classification decision is conducted using the GMMs learned during training for computing the probability that a pixel is part of the spade pads (using the spade pads GMM), or part of the background (using the background GMM). The pixel is assigned to the segment with highest probability. To illustrate, consider the two 1-dimensional GMMs shown in Figure 3-b in green and red. Assuming these GMMs were those learned during training for the spade pads (red curve) and background (green curve), the β point, with $U_β=-26$ as shown in the figure, would have a higher probability for the background GMM, and thus would be classified as background.

We summarize the classification stage as follows:

1. For the trunk to be segmented, fix the quick clamp to the trunk in the preferred position and take the picture (see Figure 2-b).
2. Convert the picture to the LUV color space and discard the L component.
3. Given the GMMs estimated during the training stage, run the classification subroutine to segment the image. This consists in determining the most probable segment for each pixel.
4. To obtain the trunk diameter, find the edge points $A$, $B$, $C$, and $D$ as shown in Figure 2-c and average them out using Eq. (1) to obtain the diameter in pixels.
5. Re-scale the diameter in pixels to the diameter in millimeters using the computed height in pixels in Eq. (2).

**B. Experimental setup**

In this section we describe the experimental setup used for confirming our main claim: that our autonomous image-based method (AIM) for trunk diameter measurement produces results with precision equivalent to those obtained with the Vernier caliper method (CM), in realistic conditions of climate and luminosity, while maintaining the operational simplicity. The two methods are contrasted through their measurement errors. To obtain these errors we require the true value of the diameter. Although there may be several approaches for obtaining such value, we decided to use a non-standard, but nonetheless precise method: the manual image-based method (MIM), which matches exactly the AIM method with the exception that the segmentation is performed manually using standard image editing software with extreme care. This method therefore avoids errors produced by the autonomous segmentation method, only introducing rounding errors caused by the resolution of camera. Pixels in this work correspond to approximately 0.1mm, equivalent to the 0.05mm precision of a Vernier caliper. For the case of AIM this results in a very convenient error that measures the error of the segmentation. For the case of CM, this error highlights the potential manual errors I, II, or IV (c.f. Table 1) caused by a careless operator conscious or unconsciously, either due to some imperfection of his senses (potentially altered by the ambient context) or by his ability and experience in taking these type of manual measurements.

For a robust evaluation we compared the two methods over several images taken in realistic conditions of ambient luminosity (affected by climate) and different experiences of the operators, on real vineyards with vertical trellising system in the experimental fields of the Plant Physiology Laboratory, Faculty of Agricultural Sciences, National University of Cuyo (Lujan de Cuyo, Mendoza, Argentina). All the pictures were taken using a NIKON COOLPIX L16 compact commercial camera, in JPEG format with a resolution of 2048x1536 pixels (3 megapixels). For the caliper measurements we used a standard, plastic, Vernier caliper with precision of 0.5mm. First the measurement of the diameter is done by manipulating the caliper to set the magnitude and then this result is recorded on notepads or paper forms. Later, information is loaded in computer spreadsheets for its posterior processing and analysis.
Operator experience experiment

In the first experiment the intent was to reproduce two realistic scenarios for our operators: inexperienced and experienced operators. The luminosity conditions were variable, taking all pictures under sunny and cloudy conditions. In the first case two operators were chosen that had no experience whatsoever on agronomic experiments but they were instructed to be extremely careful in their measurements (especially on the manual ones). The intent was to minimize the potential human error on these measurements, thus challenging the competitor AIM. The second case also consisted on two operators, but this time we chose two experienced graduate students of Agronomy Engineering of the Faculty of Agricultural Sciences that were hired and paid for their labor. This latter scenario was designed to reproduce the most common conditions under which the CM measurements are currently conducted in real-life. In both cases AIM was up to the challenge, resulting in lower errors as shown and discussed in the Results section.

For these experiments, each of the four operators conducted 7 rounds of caliper measurements (CM) over each of 30 grapevine plants, and 7 rounds of image-based measurements (AIM) over the same plants. This totaled 840 measurements per method, 210 per operator. The caliper and image measurements were taking on the same position of each plant's trunk on the position indicated by a previously positioned string as shown in Figure 2-b. Also, prior to the measurements, the bark was removed from each plant, around the target measurement position. By bark we refer to the rhytidome or dead tissue that forms around the trunk of a woody plant. In grapevine plants the bark is thick, rough and breaks off in longitudinal strips, and can represent up to 10% of the trunk diameter. By removing the bark, the observed variability in data corresponds only to the errors of Table 1.

Luminosity conditions experiment

In the second experiment the intent was to challenge our image-based method by imposing extreme solar luminosity conditions. Solar luminosity is strongly affected by climate conditions such as cloudy skies, which may change radically, even during the duration of a measuring campaign (see Figure 4). Intuitively, the experiment consisted in training the GMM model using only images of one condition type (e.g., sunny), and testing its performance by segmenting images taken during another luminosity condition (e.g., cloudy). Then, the diameters obtained were contrasted against those obtained by matching conditions, in our example segmentation of sunny images over the sunny model. Specifically, the experiment consisted in two sets of 20 images each, the sunny set taken during a sunny day, and the cloudy set taken during a cloudy day. From each set, a subgroup of 4 images was separated randomly and used for training the corresponding GMM models $M_{\text{cloudy}}$ and $M_{\text{sunny}}$, leaving a total of 16 images on each set used later for testing the autonomous segmentation (denoted $S_{\text{sunny}}$ and $S_{\text{cloudy}}$ respectively). The two models and two 16 images sets were used in two crossed evaluations. One in which the 16 sunny images were segmented using the cloudy model, denoted $S_{\text{sunny}}|M_{\text{cloudy}}$, and another where the 16 cloudy images were segmented using the sunny model, denoted $S_{\text{cloudy}}|M_{\text{sunny}}$. To assess the precision of these segmentations, each case was contrasted against the case of matching conditions, i.e., the sunny set segmented against the sunny model (instead of the cloudy one), denoted $S_{\text{sunny}}|M_{\text{sunny}}$, and the cloudy set segmented over the cloudy model (instead of the sunny one), denoted $S_{\text{cloudy}}|M_{\text{cloudy}}$. In summary: $S_{\text{sunny}}|M_{\text{cloudy}}$ tested against $S_{\text{sunny}}|M_{\text{sunny}}$, and $S_{\text{cloudy}}|M_{\text{sunny}}$ tested against $S_{\text{cloudy}}|M_{\text{cloudy}}$.

RESULTS and DISCUSSION

This section reports and discusses the results obtained for our two experiments. In both cases we report some aggregation of the absolute errors $|\text{AIM} – \text{MIM}|$ and $|\text{CM} – \text{MIM}|$ of the AIM and CM methods, respectively.

Operator experience experiment

The results for the operator experience experiments are reported in Table 2. The table shows the mean and standard deviation (in parenthesis) of the absolute error over the 420 measurements of the inexperienced operator (top), and the 420 measurements of the experienced operators (bottom).
Table 2. Mean and standard deviation (SD) of the absolute error for the caliper-based method (CM) and the autonomous image-based method (AIM), reported for two use cases: inexperienced (top) and experienced (bottom) operators.

Tabla 2. Media y desviación estándar (SD) del error absoluto para el método basado en calibre (CM) y método autónomo basado en imágenes (AIM), reportado para dos casos de uso: operarios sin experiencia (arriba) y con experiencia (abajo).

<table>
<thead>
<tr>
<th></th>
<th>Inexperienced</th>
<th>Experienced</th>
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<tbody>
<tr>
<td></td>
<td>MEAN (SD) in cm</td>
<td>MEAN (SD) in cm</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>AIM</td>
</tr>
<tr>
<td>Inexperienced</td>
<td>0.132 (0.150)</td>
<td>0.101 (0.101)</td>
</tr>
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</table>

Table 3. Results for the luminosity experiments shown in centimeters. Table (a) shows results comparing the two cloudy cases $S_{\text{Cloudy}}|M_{\text{Sunny}}$ vs. $S_{\text{Cloudy}}|M_{\text{Cloudy}}$ and Table (b) shows results for the two sunny cases $S_{\text{Sunny}}|M_{\text{Cloudy}}$ vs. $S_{\text{Sunny}}|M_{\text{Sunny}}$.

Tabla 3. Resultados para los experimentos de luminosidad mostrados en centímetros. La Tabla (a) muestra los resultados comparando los casos $S_{\text{Cloudy}}|M_{\text{Sunny}}$ vs $S_{\text{Cloudy}}|M_{\text{Cloudy}}$ y la Tabla (b) muestra los resultados para los dos casos $S_{\text{Sunny}}|M_{\text{Cloudy}}$ vs $S_{\text{Sunny}}|M_{\text{Sunny}}$.

(a) | Mean | SD |
<table>
<thead>
<tr>
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<tbody>
<tr>
<td>5.027</td>
<td>5.067</td>
<td>5.012</td>
</tr>
<tr>
<td>5.021</td>
<td>4.982</td>
<td>4.973</td>
</tr>
<tr>
<td>0.006</td>
<td>0.085</td>
<td>0.039</td>
</tr>
</tbody>
</table>

(b) | Mean | SD |
<table>
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<tr>
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<tbody>
<tr>
<td>5.014</td>
<td>5.018</td>
<td>5.066</td>
</tr>
<tr>
<td>5.069</td>
<td>5.074</td>
<td>5.174</td>
</tr>
<tr>
<td>0.055</td>
<td>0.056</td>
<td>0.108</td>
</tr>
</tbody>
</table>
The results show that in both cases (experienced vs. inexperienced), the mean errors are smaller for AIM, with 0.101cm against the 0.132cm of CM for the inexperienced case, and 0.126cm against 0.136cm for the experienced case. The same holds for the standard deviations, with 0.101cm for AIM against 0.150cm for CM in the inexperienced case, and 0.097cm for AIM against 0.139cm for CM in the experienced case. A larger standard deviation implies that it is more probable for AIM to have errors closer to the (smaller) mean. The results also show another interesting fact: the AIM error decreases for inexperienced operators, while the CM is maintained. These results prove, at least empirically, not only that our method is not affected by the experience level of the operator (and even improves slightly), but it is equivalent (slightly better) to the manual caliper method.

To conclude we presents a more detailed analysis of the outliers that produce the higher standard deviation of the CM method. For that we computed a histogram that counts the number of errors that each method presents on each diameter value. For simplicity we do not show the full histogram but instead highlight some outstanding facts. First we note that of all 840 cases, 62.2% of the CM measurements are smaller than the maximum mean 0.136cm, while AIM has 7.2% more cases within that range, i.e., 69.4%. Also, all the cases of the AIM method are smaller than 0.62cm, while only 98.6% of the CM measurements fall within that interval, with the remaining 1.4% reaching errors of up to 1.8cm. The 1.4% of 840 represents 12 measurements, which cannot be overlooked easily, and whose most probable cause is human error due to operator carelessness or fatigue.

Luminosity conditions experiment

The results for the luminosity conditions experiment are shown in Table 3 (in centimeters). The Table shows the comparison of the two cloudy cases $S_{cloudy}$ vs. $S_{sunny}$ (Table 3-a on top) and the comparison of the two sunny cases $S_{sunny}$ vs. $S_{cloudy}$ (Table 3-b on the bottom), for each of the 16 images, together with mean and standard deviation over the 16 images on the right. Both cases show a mean of approximately 0.04cm, a small discrepancy considering the errors of AIM (as shown in the previous experiment) are approximately 0.10cm. Therefore, we can conclude that, at least empirically, the segmentation algorithm is robust to changes in luminosity caused by cloudy skies. This justifies using a single, mixed luminosity GMM model for both luminosity conditions, as it was the case for the first experiment.

CONCLUSIONS

This paper has presented a high-precision and low-cost method based on Computer Vision for autonomous measurement of trunk diameter on grapevines from images acquired with a compact digital camera. This method is an important contribution in the field of autonomous sensing of complex variables in Precision Agriculture. In practice, generally, the trunk diameter is measured manually using Vernier calipers. This method involves human errors that can occur during measurement campaigns due to fatigue, haste or carelessness. There are several studies that address the problem of automating the measurement of trunk diameter trees. However, these solutions are not optimal: some are low cost but low precision (or equivalently high failing rate), and others are high precision but high cost. The experimental analysis for our method shows that it is more accurate than the manual method based on caliber, mainly because it is more robust to human error. An important advantage over other authors named in this work, is that the technology required to implement this method is cheap and probably any agronomist already has some of the main elements: a standard desktop computer and a low-resolution digital camera (3 megapixels). In addition, our method has two advantages over the manual method: avoid mistakes I, II, and IV, summarized in Table 2; and eliminates the qualifications of the operator as a factor of influence in results, i.e., it requires people with little or no knowledge and experience in agronomy experiments.

It is worth noting some open problems around the method proposed in this paper. Our method is still prone to error III of Table 2, since plants are not identified autonomously, still requiring a human to associate a photo ID with the plant. This is not difficult to automate however. For example, one solution is to include QR codes (28, 29) in the scene to identify automatically the plant of the image. This approach has been omitted in this work. In addition, automation of the measuring process such as trunk diameter makes it amenable to further automation. On one hand it may be embedded in an unmanned (air or land) vehicle that autonomously navigates the field taking measurements. On the other hand, it may be embedded in an information system for the management of experiment...
campaigns that integrates the workflow for the whole agronomic experiment. Such a system could incorporate all the benefits of current technologies such as mobile photography and computing, GPS positioning, databases, web-based interfaces, and more (34, 38). This proposal is beyond the scope of this work. However, some members of our laboratory are working on a full report of this framework, including automated matching of plant and image. Finally, with the setting presented in this work, the errors incurred by the GMM algorithm are given only over a corrupted zone, corresponding to edges of the spade pads in the images. In Figure 2-c the error by corrupted zone is approximately 9 pixels corresponding to 0.9mm, but this value can vary depending on the images. Such error is caused by 3 main sources: imperfections of materials used in spade pads of the clamp; presence of high brightness over the edges of spade pads; information loss due to JPEG compression algorithm. Thus, our approach may greatly benefit by simple technical improvements such: smaller and easily manipulable clamp; possibility to include multiple clamps in the same image; and better materials for the spade pads that better resists wear and tear, thus reducing segmentation errors.

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ACKNOWLEDGMENTS

This work was funded by the scholarship program of the National Technological University (UTN) and the National Fund for Scientific and Technological Promotion (FONCyT) of Argentina. We thank the Department of Plant Physiology, Faculty of Agricultural Sciences, Uncuyo, for offering their vineyards to capture the images used in this work.

APPENDIX A: Image Segmentation

Image Segmentation is to partition an image into a set of non-overlapping regions, which have a consistent semantics about a particular application (46). Ideally are expected that regions represent an object or parts of it. The extracting process from domain of one or more image regions, which satisfy a uniformity or homogeneity criterion, is mainly based on the characteristics derived from color space. This process can be enhanced by some additional knowledge about the objects in the scene, such as geometric and optical properties (31). Formally, the segmentation process is defined as a method to partitioning an image \( I \) in regions \( R_k \), with \( k = 1, \ldots, K \), such that each region \( R_k \) is a candidate object (20):

**Definition 1.** A region is a subset of pixels in an image \( I \).

**Definition 2.** Segmentation is the grouping of pixels into regions, such that:

- The regions \( R_k \) form a partition, i.e., they encompass the whole image and do not overlap each other.
- Each region \( R_k \) satisfies uniformity criteria (all pixels in the region have one or more common properties).
- The pixels belonging to adjacent regions, when taken together, do not satisfy the uniformity criterion.

With these definitions, the uniformity criterion is the most important element of this model, and can be as simple as uniformity in the color intensity of the pixels, while generally is more complex, often depending on the application.
APPENDIX B: Color Spaces

Generally, the pictures taken with conventional digital cameras are in the RGB color space, which means that the color of a pixel is represented as a point in 3-dimensional space comprising the intensities of the red (R), green (G), and blue (B) component (20, 48). From combination of these intensities any color can be represented. RGB is suitable for color display (television systems and digital cameras), but not usually suitable for task analysis and image segmentation. This is due to the high correlation between R, G, and B, i.e., if you change the intensity or brightness of a pixel, the three components change accordingly. Moreover, color measurement in the RGB space not represents color differences in a uniform scale; therefore, it is impossible to evaluate the similarity of two colors from the distance in the RGB space (13). However, the RGB representation can be derived other color spaces by using linear or non-linear transformations. Color spaces such as RGB, HSI, HSV, LUV, LAB, etc., are used in image segmentation, but none of them is superior to the other in all kinds of images, and often depends on the problem (20, 48). In this paper, the original images were converted from RGB to LUV \((L=\text{luminescence}, \ U=\text{saturation}, \ V=\text{hue angle})\). LUV separates the color information of an image from intensity information. Color information is represented by a tone (V) and saturation values (U), while the intensity, which describes the brightness of an image is determined by the amount of light (L). Thus LUV has several advantages over RGB: we can control the color information and the intensity of a way simpler and independent; we allows to directly compare two colors based on geometric separation in color space, therefore, is especially efficient to the measurement of small differences in color; and we reduces dimensionality problem, since in this work only the color information (UV components) is used, discarding intensity information (component L) (13, 20, 48).