Use of Hough Transform and Homography for the Creation of Image Corpora for Smart Agriculture

Jose A. Brenes[1], Javier Ferrández-Pastor[2], José M. Cámara-Zapata[3], and Gabriela Marín-Raventós[1]

[1] CITIC/ECCI/PPCI, University of Costa Rica, San José 11501, Costa Rica
joseantonio.brenes@ucr.ac.cr, gabriela.marin@ucr.ac.cr
[2] I2RC, University of Alicante, Alicante 03690, Spain

[3] CIAGRO-UMH, University Miguel Hernández, Alicante 03202, Spain

Abstract. In the context of smart agriculture, developing deep learning models demands large and high-quality datasets for training. However, the current lack of such datasets for specific crops poses a significant challenge to the progress of this field. This research proposes an automated method to facilitate the creation of training datasets through automated image capture and pre-processing. The method's efficacy is demonstrated through two study cases conducted in a Cannabis Sativa cultivation setting. By leveraging automated processes, the proposed approach enables to create large-volume and high-quality datasets, significantly reducing human effort. The results indicate that the proposed method not only simplifies dataset creation but also allows researchers to concentrate on other critical tasks, such as refining image labeling and advancing artificial intelligence model creation. This work contributes towards efficient and accurate deep learning applications in smart agriculture.

Keywords: Dataset Creation, Image Capturing and Pre-processing, Homography, Hough Transform, Smart Farming.

1 Introduction

We are experimenting with an Artificial Intelligence (AI) boom where models have shown an unprecedented potential to address distinct challenges and improve everyday life in multiple fields. AI applications flourish daily in areas like Education, Entertainment, Customer Services, Industry, and Agriculture. However, the success and performance of these AI models are highly dependent on the quality and quantity of the data available to train them [1].

There is a shortage of high-quality datasets for training AI applications. Although it is possible to access a few public datasets in distinct areas of application [2, **?**], there is still a lack in other areas. In many domains, the existing datasets may be limited, outdated, or not cover all possible variations of the problem to be solved. Therefore, creating new datasets becomes essential to cover a greater range of real-world scenarios and situations.

Furthermore, in some emerging and specialized areas, such as medicine and robotics, specific and properly annotated data is scarce or expensive to obtain. In this context, generating new datasets can open new opportunities to train models that address specific challenges in these fields and, ultimately, improve decision-making.

The scarcity of public datasets in smart farming is not asunder of the trend. It remains a crucial bottleneck for creating computer vision and machine learning applications in this domain [2]. Although it is possible to use technologies like drones to obtain large volumes of data from the field, it is not always possible. Very restricted crops make it difficult to get

Dhinaharan Nagamalai (Eds): NLAII, VISCOM, CCSITA, AIDD, BCYIoT -2023
pp. 09-19, 2023. IJCI – 2023 DOI:10.5121/ijci.2023.120602

data from cultivations. Still, there are also cultivation methods that make it challenging to gather imaging data in fields, like cultivation under greenhouses.

Since data scarcity is a major challenge when training AI and deep learning (DL) models [4], creating new training datasets becomes a motivation to continue advancing in the research and application of AI. Another key reason to create new datasets lies in ethics and fairness. Deep learning models can be affected by inherent biases in the training data. By designing more diverse and balanced datasets, bias propagation can be reduced and promote greater effectiveness and fairness in AI applications.

In this paper, we propose an automated method to capture image datasets for smart farming AI applications. We propose a method to capture and pre-process the images, taking into consideration adjustable time slots. This enables us to get a large volume of clean and different images. This way, we avoid using augmentation techniques to train AI models.

We used the proposed method in two study cases: first, we created a germination dataset containing images of plants growing in seedbeds. In a second study case, we created an image dataset of plants in different growing stages. Currently, we are working on separate projects using the created datasets to train deep learning models to classify new samples.

The structure of this paper is as follows: first, we present related works about dataset creation in distinct domains and some reviews related to publicly available datasets in the area of smart farming applications. Next, we present our proposed method to automate the capture and pre-processing of images for smart farming AI applications. Following, we present the results obtained in two study cases related to creating image datasets. Finally, we present some conclusions about the conducted research and future work.

2 Related work

Some studies analyzing the data scarcity of training datasets for AI applications have been conducted. We consider it important to highlight some of them. First, the study presented in [1] analyzes the problem derived from using the currently available datasets to train models leaving aside the data quality and avoiding creating new ones. The authors demonstrated this by using probabilistic models to estimate the quantity of data available in the coming years. This way, the authors conclude that by around 2030 and 2060, AI progress will probably slow down due to data scarcity.

In a recent study [4], authors present the problem related to data scarcity when training AI models. In this study, authors also propose some solutions to data scarcity: (1) Transfer Learning to take advantage of pre-trained models and re-applied them to new models, (2) Self-supervised Learning to use large amounts of unlabelled data and small amounts of annotated data, (3) Generative Adversarial Networks as a tool to generate new data samples with similar features as the real input data, (4) Model architecture, as a way to reduce the complexity of the model to require fewer amounts of training data, (5) Physics-informed neural networks, as a deep learning technique that can deal with insufficient training data, and (6) Deep synthetic minority oversampling technique, to generate synthetic images to address the problem of imbalanced data. Nevertheless, the authors do not mention, as a solution, the possibility of creating new custom-made datasets, which we consider the better option if possible.

From the study mentioned above, we also rescue an essential statement. The authors pointed out a list of tips for reporting datasets. We consider this crucial because if the details of the used dataset are clearly stated, it makes it possible for the reader of the study to know about its origin, availability, and other technical details.

Regarding the availability of datasets, in [2], the authors described a list of public image datasets in the precision agriculture domain. In the study, the main characteristics of 34 datasets are analyzed: 15 datasets on weed control, ten datasets on fruit detection, and nine datasets on miscellaneous applications. Besides, the authors concluded that the presented survey can be valuable for researchers when they have to select an image dataset to create new models. Furthermore, the study reveals the areas where the creation of new datasets to support smart farming is needed.

No studies were found about techniques or systematic methods for creating new datasets for smart farming. Nevertheless, some studies in other domains do describe them. In [5], authors present a methodology based on processing screenshots to create an image dataset for training Google's t-rex game. Meanwhile, authors in [6] propose a framework developed to create human pose datasets, including camera calibration, refined human pose estimation, and manual annotations.

The relevance of these studies relies on the systematization of the capturing method and pre-processing of samples. We consider both requirements for our proposal. In the next section, we present our proposed method to automate the capture and pre-processing of images for smart farming AI applications.

3 Automating the capture and pre-processing of images in smart farming

Most image datasets available for smart farming analyzed in [2] have problems like the dataset size and the samples' size. The first is related to the number of samples included in the dataset, while the second is related to the size in pixels of each sample. We deal with both problems in our proposal by accomplishing two requirements: (1) automating the capture of the images and (2) processing the images to resize them as required.

To address the first requirement, we prepared a setup for image acquisition. It uses a low-cost camera (Arducam 64MP Auto-focus camera, which can take images of 9152x6944 pixels) and a Raspberry Pi to control it. We place and fix the camera and the Raspberry Pi inside a greenhouse. Then, we created a Python script to manage the distinct camera options (focus, zoom, size, among others) and to capture the images automatically. This way, we can adjust the camera sensor according to the climate conditions and schedule the capture of the images. After some tests, we discovered that under greenhouse conditions, the camera sensor takes a maximum of twelve seconds to take each picture. Thus, we could easily take at least one image every fifteen seconds.

Fig. 1 shows the camera setup inside the greenhouse. It is crucial to note that our proposed method requires placing circle reference markers containing the study area. In Fig. 1, reference markers are detailed as pink circles delimiting various plant pots. These reference markers will be used to pre-process the captured images as it is described below.

As seen in Fig. 1, we can rotate the camera to take zenithal or side images. Besides, since the Raspberry Pi runs Linux and can be connected to the network, we can access it through SSH protocol to remotely control it. Using the operating system task scheduling tool, we take advantage of these conditions to schedule the image acquisition. Thus, we only need to create the script to control the camera, and we can schedule its execution easily. Nevertheless, the image acquisition process takes two phases: the image capture and the pre-processing of that image.

Regarding the image capture phase, the next code shows the Python program capturing the images.

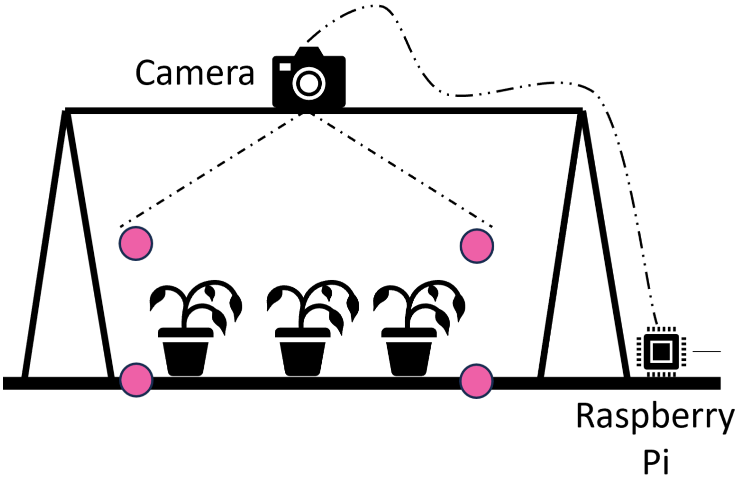


Fig. 1. Camera setup in the greenhouse.

Listing 1.1. Python script that controls the camera

```
#!/usr/bin/python3
import time
from picamera2 import Picamera2, Preview
picam2 = Picamera2()
picam2.rotation = 180
picam2.vflip()
picam2.start_preview(Preview.NULL)
preview_config = picam2.create_preview_configuration(main={"size"
    ↪ :(5568,3132)}, buffer_count=2)
picam2.configure(preview_config)
picam2.start()
time.sleep(1)
picam2.set_controls({"AfTrigger": 1})
time.sleep(10)
date_time = time.strftime("%Y%m%d_%H%M%S")
image_filename = "image_"+date_time+".jpg"
picam2.capture_file(image_filename)
```

Once the image has been taken, the process's second phase occurs. Since manually resizing and cutting the images can produce bad samples, we decided to automate this process. In addition, we discover that due to temperature changes inside the greenhouse, the camera suffers little movement during the day and night, resulting in displaced images, which makes it even more difficult to resize and cut manually. Thus, the second phase of the process runs on the Raspberry Pi and uses mathematical functions like Homography, HoughCircles, and the Python library OpenCV to clean, rectify, and cut the image as needed.

Algorithm 1 shows the steps necessary to achieve that.

Regarding the two mathematical functions that intervene in the pre-processing of images, we use the Python library OpenCV that implements both functions.

HoughCircles is based on the Hough Transform, a technique originally developed to detect lines inside an image. This function enables the detection of circles in an image based on the Hough Transform, and the method proposed in [7]. One of the highlights of

Algorithm 1 Image pre-processing

Require:

Image $I = captured\_image$

Number_of_rows $r = n$

Number_of_columns $c = m$

procedure PRE-PROCESS(I, r, c)

  Make a temporal copy of the image $temp$=I

  Convert $temp$ to HSV color scale

  Apply a color mask to $temp$ with the color of reference points

  Convert $temp$ to gray-scale

  Apply HoughCircles function to $temp$ to get the coordinates of reference points in the image $coordinates$=$\{\{x_1, y_1\}, \{x_2, y_2\}, \ldots \{x_n, y_n\}\}$

  if $coordinates$ mod $4 = 0$ **then**

    Apply the OpenCV Homography function by using $coordinates$ points

    Save the resulting image as $rectified$

    if $r > 0$ AND $c > 0$ **then**

      for i={0,...,n} **do**

        Cut the image $rectified$ by i

        Save the resulting image as row_i

        for j={0,...,n} **do**

          Cut the image row_i by j

          Save the resulting image as $cell\_i\_j$

        end for

      end for

    end if

  else

    Log an error for image I

  end if

end procedure

HoughCircles is its ability to efficiently handle circles with different sizes and noise levels in the image, which in our case, is necessary to deal with.

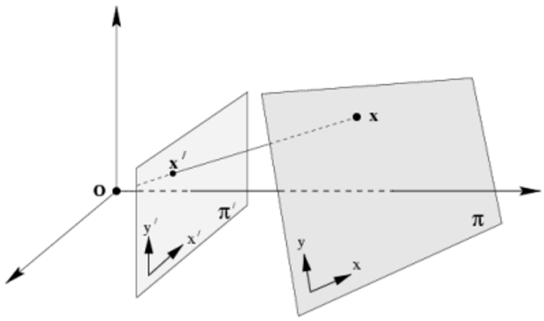
When we pre-process the captured image, we first apply a mask to get only the content similar to the color of the reference markers. Thus, we filter all the other elements in the image to facilitate the recognition of the reference markers. Since the reference markers are circle shaped, we can use the HoughCircles function to detect their x and y coordinates in the image. Each image must have at least four reference markers. However, it is possible to get more than four coordinate pairs. In those cases, we log an error to process the image manually.

Homography is a geometric transformation that maps points in one image to corresponding points in another, keeping the same center of projection and the alignment of the elements in the image [8]. The homography method is the most general formulation of linear transformations in projective geometry. For this reason, it is also known as a projective transformation [9].

As shown in Fig. 2, the Homography is represented by a 3x3 matrix that relates points in one image to their corresponding points in another. The homographic matrix is computed from at least four corresponding points between the source and destination images, employing least squares or RANSAC algorithms to obtain an accurate transformation for various practical applications.

Our proposal uses the homography function to rectify the captured image before cutting it into individual images.

After running the pre-processing phase, getting images containing individual samples of the study objects is possible. These images differ from one research to another. For example, if the analysis is focused on plant stems, it could be possible to get side images



$$\begin{pmatrix} x'_1 \\ x'_2 \\ x'_3 \end{pmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$

Fig. 2. Homography planar projective transformation [8].

containing individual plants in pots. To do that, it is only required to place the reference markers in the desirable position and wait for the result images.

It is also crucial to note that adjusting the name of the resulting images can also help in the labeling of the samples. The proposed method covers only the capturing and pre-processing of samples. Therefore, if needed, it is required to label the resulting images manually.

4 Results

We conducted two study cases to evaluate the proposed method of capturing and pre-processing image samples for smart farming. Following, we detail the study cases.

4.1 Study case 1: germination of plant growing in seedbeds

In this case, the objective is to determine the germination stage of Cannabis Sativa plants. We attempt to create a classifier to recognize the state of plants in a seedbed in real time. This way, we can easily know the percentage of germinated plants in the seedbed.

To achieve that, we need an image dataset of Cannabis Sativa plants germinating in a seedbed at distinct growing stages. After a literature review, image datasets containing samples of Cannabis Sativa germination have not been found. Although it is possible to get image datasets containing plants for other species in the germination stage, those datasets focus mainly on weed detection. Since we work in a greenhouse-controlled environment, we seek to classify only images of the plants leaving aside the weed presence.

For this reason, we decided to create a new custom dataset. We work with seedbeds where it is possible to plant 72 seeds simultaneously. But there was a problem related to the processing of the captured images. Initially, we had to cut the images manually, which caused bad samples. Secondly, we had to deal with every movement suffered by the camera. Thus, every captured image must be manually rotated to align it and make cutting possible. So, the whole process was too slow and stressful.

However, using the proposed method, we could create a clean and extensive dataset containing more than 80000 images of 224x224 pixels, containing data of plants in different germination stages. Fig. 3 shows an example of the captured image and the resulting samples.

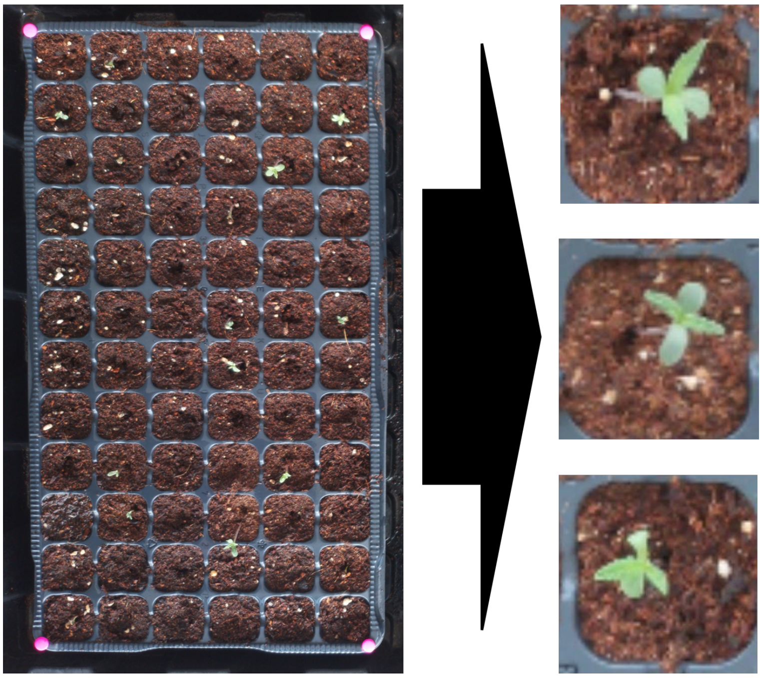


Fig. 3. Seedbed and samples obtained after running the proposed capturing and pre-processing method.

Currently, we are labeling the samples to train a deep-learning model and publish the study results and the dataset. The proposed method was very easy to use because of the automation of the script.

Having many plants in the seedbeds, we selected some and put them to grow in pots. With these plants, we run another study case to analyze the growth of the plants. This second study case will be detailed next.

4.2 Study case 2: modeling plants in different growing stages

For the second study case, we took side images of the plants in the pots. In this case, we try to analyze the growing stages of the plants. The objective was to analyze individual parts of the plants, like stems, leaves, or flowers.

From the literature [10], we can see that two open areas of research in smart farming are related to using artificial intelligence techniques to count leaves, flowers, and fruits automatically and the approximation of stem width through machine learning techniques. We can contribute to that area by using deep learning techniques and an image dataset containing samples of plants, leaves, flowers, fruits, and stems.

However, we suffer again from the scarcity of available training data. Although it is possible to find datasets containing samples of plant parts for some crops, they are not available for many other crops like Cannabis Sativa, making it necessary to work on the creation of new custom datasets.

This way, we work on the creation of a second dataset. By knowing the distance between the camera and the plants, it is possible to approximate the stem width. It is important to highlight that to count leaves, flowers, and fruits; it is better to relocate the camera to the zenithal position and take samples from that location. Hence, we created a second dataset to analyze only the stem of plants.

Fig. 4. Sample obtained after running the proposed capturing and pre-processing method for stem analysis.

Fig. 4 shows an image after running the capturing and proposed pre-processing method. For side images, it is crucial to place a uniform white wall or screen behind the plants. The uniform color helps to get images where the plant is highlighted, and there is not any other distraction altering the resulting image. It is also required to place the reference markers in a position that makes it possible to capture the whole plant. It is important to note that at the beginning, there could be a lot of blank space in the image. However, this way, we can get a dataset of comparable images, making it possible to generate a time-lapse of the plant growing.

Moreover, if we plan to analyze the stem growth and width, it is required to keep the camera and the reference markers in the same position throughout the entire process. In the proposed method of capturing and pre-processing, neither the camera nor the reference markers move. In this case, we only have to guarantee keeping the position of the plant pots.

Since we are analyzing plants' growth, the second study case takes more time to be completed. Nevertheless, we can approximate the size of the resulting dataset considering the time period defined for the image capturing and the number of pots appearing in the images. For the second study case, we defined an image capture every four hours from 8:00 to 16:00. This decision was made because we were analyzing the growth of the plants, so we did not need images so closely in time. This way, we can get three daily images, each containing four pots. After the pre-processing of the images, we got twelve samples every day. Considering that the growing phase of the Cannabis plants can take approximately four months, we can get a dataset composed of 1440 image samples.

From the two executed study cases, we want to highlight that the resulting image samples are individual and unique. We do not recur to augmentation techniques. We only preprocess the original captured images following the proposed method. Besides, our method enables us to get clean and high-quality datasets, where the samples' size is usually bigger than the needed by deep learning models, making it possible to re-scale the images as needed.

In the next section, we present the conclusions resulting from this work. We also state some ideas we consider can be done in future work.

5 Conclusions and future work

The scarcity of datasets for training deep learning models highlights the importance of creating initiatives to share and release public datasets, encourage research collaboration, and establish more efficient and consistent data collection and labeling practices. To deal with scarcity, creating new high-quality training datasets is necessary. Nevertheless, this task is very hard to achieve because it requires to guarantee that datasets accomplish size, resolution, and volume adequate for complex models.

We consider that automating the capture and preprocessing steps can reduce the effort required to create new datasets, enabling the researchers to focus on other important activities like labeling and creating the models.

In this paper, we proposed a method to ease the creation of image datasets for smart farming applications. The proposed method enables capturing and preprocessing images automatically and periodically. This way, getting a large volume of images from an individual setup is possible.

With the proposed method, we contribute to creating new datasets for training smart farming AI models. During this research, we conducted two study cases in which we can use the proposed method to create new datasets. First, the germination dataset is currently being used to train a deep-learning model to identify the germination of Cannabis Sativa plants in seedbeds in real-time. Meanwhile, a second study case produces a dataset containing images of plants at different stages of growth. This dataset will be used to analyze the plants' stem width and create a model of the growing plants.

The results obtained from using the proposed method are very positive since we try to manually execute the capturing and pre-processing of images, resulting in a stressful and slow task. With the proposed method, creating the dataset while doing other activities is possible.

Besides, the proposed method enables the researcher to adjust the name of the resulting images, easing the labeling phase of the dataset creation. By selecting the correct name for the resulting images, it can be possible to get datasets partially labeled, reducing the work of labeling tasks.

Creating new training datasets is an ever-evolving, collaborative effort involving data scientists, researchers, and engineers. By investing in the generation of high-quality and relevant data, we make possible the development and continuous improvement of deep learning models that can overcome complex challenges and offer innovative solutions for the advancement and benefit of society.

We plan to use the proposed method outside the greenhouse in future work. In this case, the most challenging task is to place and keep the reference markers in the same position. However, we consider that our proposal could be very helpful with crop production in outdoor environments.

Acknowledgements

This work was partially supported by the Research Center for Communication and Information Technologies (CITIC) and the School of Computer Science and Informatics (ECCI) at the University of Costa Rica, Research Project No. 834-B9-189. This study is part of the AGROALNEXT program (AGROALNEXT/2022/048) and has been supported by MCIN with funding from the European Union NextGenerationEU (PRTR-C17.I1) and the Generalitat Valenciana.

References

1. P. Villalobos, J. Sevilla, L. Heim, T. Besiroglu, M. Hobbhahn, and A. Ho, "Will we run out of data? an analysis of the limits of scaling datasets in machine learning," 2022. [Online]. Available: https://arxiv.org/abs/2211.04325
2. Y. Lu and S. Young, "A survey of public datasets for computer vision tasks in precision agriculture," Computers and Electronics in Agriculture, vol. 178, p. 105760, Nov. 2020. [Online]. Available: https://doi.org/10.1016/j.compag.2020.105760
3. M. J. Pappaterra, F. Flammini, V. Vittorini, and N. Besinovi ˘ c, "A ´ systematic review of artificial intelligence public datasets for railway applications," Infrastructures, vol. 6, no. 10, p. 136, Sep. 2021. [Online]. Available: https://doi.org/10.3390/infrastructures6100136
4. L. Alzubaidi, J. Bai, A. Al-Sabaawi, J. Santamar´ıa, A. S. Albahri, B. S. N. Al-dabbagh, M. A. Fadhel, M. Manoufali, J. Zhang, A. H. Al-Timemy, Y. Duan, A. Abdullah, L. Farhan, Y. Lu, A. Gupta, F. Albu, A. Abbosh, and Y. Gu, "A survey on deep learning tools dealing with data scarcity: definitions, challenges, solutions, tips, and applications," Journal of Big Data, vol. 10, no. 1, Apr. 2023. [Online]. Available: https://doi.org/10.1186/s40537-023-00727-2
5. D. Bajpai and L. He, "Custom dataset creation with tensorflow framework and image processing for google t-rex," in 2020 12th International Conference on Computational Intelligence and Communication Networks (CICN), 2020, pp. 45–48.
6. R. R. Barioni, W. L. Costa, J. A. C. Neto, L. S. Figueiredo, V. Teichrieb, J. P. Quintino, F. Q. B. da Silva, A. L. M. Santos, and H. Pinho, "Hutrain: a framework for fast creation of real human pose datasets," in 2020 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct), 2020, pp. 65–66.
7. H. Yuen, J. Princen, J. Illingworth, and J. Kittler, "Comparative study of hough transform methods for circle finding," Image and Vision Computing, vol. 8, no. 1, pp. 71–77, Feb. 1990. [Online]. Available: https://doi.org/10.1016/0262-8856(90)90059-e
8. R. I. Hartley and A. Zisserman, Multiple View Geometry in Computer Vision, 2nd ed. Cambridge University Press, ISBN: 0521540518, 2004.
9. R. Zeng, "Homography estimation: From geometry to deep learning," Ph.D. dissertation. [Online]. Available: https://doi.org/10.5204/thesis.eprints.134132
10. J. Brenes, A. Mart´ınez, C. Quesada-Lopez, and M. Jenkins, ´ "Decision support systems that use artificial intelligence for precision agriculture: A systematic literature mapping [sistemas de apoyo a la toma de decisiones que usan inteligencia artificial en la agricultura de precision: Un mapeo sistem ´ atico de literatura]," ´ RISTI - Revista Iberica de Sistemas e Tecnologias de Informacao, vol. 2020, no. E28, pp. 217–229, 2020, cited By 0. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0- 85081021329partnerID=40md5=a6d1e4a4fc59451683aec961b6576192

Authors

Jose A. Brenes received his Master in Computer Science from the University of Costa Rica. He did a degree in computer science at the University of Costa Rica. He is pursuing his PhD in Computer Science from the University of Costa Rica and the University of Alicante. His research interests include Smart farming, Computer networks, Human-Computer Interaction, and Information Technology Management.

Gabriela Marín-Raventós received a MSc in Computer Science from Case Western Reserve University and a Ph.D. in Business Analysis and Research from Texas A&M University, United States. She did a degree in Computer Science at the University of Costa Rica. His research interests include Smart Cities, Human-Computer Interaction, Decision Support Systems, Gender in IT, and Digital Equity.

Javier Ferrández-Pastor received Ph.D. from the University of Alicante, Spain. He did a degree in Industrial Engineering at the University of Oviedo, Spain. His research interests include Information, communication and control technologies, Monitoring and control applications, and Artificial Intelligence.

José M. Cámara-Zapata received Ph.D. from the University Miguel Hernández of Elche, Spain. He did a degree in Agricultural Engineering at the Valencia Polytechnic University, Spain. His research interests include Monitoring, Modeling, and Control applications.