agronomy

Editorial

Application of Image Processing in Agriculture

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1. Introduction

Agriculture will face significant challenges in the 21st century to feed a record number of people and animals and generate resources for industry (for example, wood, cellulose, and energy); thus, it is essential increasing yield and reducing pollution, water consumption, and energy consumption. UN (United Nations) studies project a world population of 9.8 billion inhabitants in 2050, a growth of 26% compared with the current population. One of the significant challenges to ensure the availability of quality food in light of the increasing global population, the scarcity of water, and the depletion of arable land is to improve the agricultural production system sustainably, in compliance with four of the UN Sustainable Goals [1]. This improvement implies assimilating appropriate technologies that promote an increase in productivity and agricultural sustainability associated with a change in strategy based on the concept of smart farming, which requires up-to-date knowledge of agricultural systems and the agents involved in the production process.

A key technology for such developments is image processing, a discipline that plays an important role in the management of the majority of agronomic systems. Images are remotely collected and processed with high frequency, providing spatial resolution according to the user's requirements. With the dissemination of low-cost and high-resolution optical sensors, the range of applications is growing rapidly, requiring more research to cope with these data types. The miniaturisation of multispectral and hyperspectral sensors and their reduced costs have also unveiled new perspectives for applications in agriculture. There is a growing interest in new techniques for processing high-resolution images collected with RGB, multispectral, and hyperspectral sensors from the air (with UAVs, for instance) or ground to overcome agricultural challenges. Image processing and analysis techniques, for instance, classification and machine learning methods, are crucial for the extraction of appropriate data.

2. Overview of the Special Issue

This Special Issue covers this broad field of research, namely image processing applications in agronomy. Fifteen research papers were published, in which scholars utilised several distinct image acquisition devices, carrier platforms, and processing pipelines.

Regarding the type of acquisition sensor, Moryia et al. [2] and Iost Filho et al. [3] used lightweight hyperspectral cameras, the latter with unmanned aerial vehicles (UAVs) and the former with proximal collection. Moryia et al. [2] assessed existing spectral indices and proposed a new index, the AERI (Anthocyanin Red Edge Index), for the detection of sugarcane plants affected by mosaic virus with hyperspectral images collected with UAV. Iost Filho et al. [3] used proximal hyperspectral images to assess the injuries caused by various densities of infestation by four pests in soybean plants.

Multispectral cameras onboard unmanned aerial vehicles (UAVs) are very common in recent times and were considered in several papers published in this issue. Näsi et al. [4] used 27 multispectral and RGB images acquired with UAVs to assess their association with soil quality indicators, concluding that soil indicators explain the variability in UAV images in the majority of cases. Sarkar et al. [5] assessed several vegetation indices derived from

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multispectral aerial images collected with a UAV, for indirect phenotyping of peanut crops to identify resistant germplasm under water stress. Soares et al. [6] developed a method for the early detection of coffee leaf rust using multispectral images acquired with UAV using a support vector machine (SVM) algorithm. Oliveira et al. [7] analysed UAV-collected RGB images to monitor dry matter yield (DMY) and nitrogen concentration in grasslands with four deep regression methods.

Close-range (proximal) image acquisition has become more efficient due to the widespread use of lightweight multispectral and smartphones. In several contributions, researchers used close-range images with distinct image processing techniques to provide solutions to various applications. Gonçalves et al. [8] used mobile devices to acquire RGB images for pest monitoring in viticulture, with further analysis using five different deep-learning models. Cabrera et al. [9] also used images collected with mobile cameras to acquire images of rice grains, aiming to determine the moisture content with classification and regression algorithms. Renfroe-Becton et al. [10] used images collected with smartphones and RGB cameras to develop a technique for diagnosing peanut foliar symptoms based on image classification and regression models. Vieira et al. [11] used an existing image dataset of close-range images of leaves from several plant species [12] to develop a method to estimate the percentage of damaged leaf areas consumed by insects. Carreira et al. [13] developed two techniques based on proximal RGB images to assess intra-row spacing. The images were analysed with image processing techniques with experiments conducted in maise plantations. Souza et al. [14] developed a technique to predict the colour intensity of flowers based on the plant canopy's external shape, which was extracted from close-range RGB images and analysed with image processing algorithms. Moreira et al. [15] used micrograph images of pellets of agricultural residuals acquired with a ZEISS Stemi-305 microscope with further image processing techniques to predict adsorption at microstructural stress.

Multispectral images collected using orbital platforms are the most common source of data for many agriculture applications owing to the larger area covered, the quality and reliability of radiometric values, and the temporal frequency. Abreu Júnior et al. [16] used Sentinel-2 images with a machine learning algorithm to estimate the yield of a coffee crop, concluding that the neural network was the most accurate algorithm for this task. Bautista et al. [17] analysed the impacts on rice crop productivity with the use of biostimulants based on Sentinel-2 and Planet images.

3. Conclusions

This Special Issue encompasses many different applications in agriculture with various sensors and platforms, for instance, close-range devices such as microscopes, smartphones, and professional RGB cameras; UAV-based devices with RGB, multispectral, and hyperspectral features; and satellite-collected multispectral imaging platforms. The value of digital images with suitable processing is undoubtedly evident as they are incorporated into daily use to improve productivity and reduce costs and inefficiencies.

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