Design of a fuzzy controller for LED lighting systems using leaf area estimated through digital image processing

Diseño de un controlador difuso para sistemas de iluminación LED utilizando área foliar estimada mediante procesamiento digital de imágenes

María José Herrera Hernández[1], Marcos Jesús Villaseñor Aguilar[1], Miroslava Cano[1], Carlos Guastavo Manríquez Padilla[2], Alejandro Barrientos García[3], Vignaud Granados Alejo[3]

[1]Maestría en Ingeniería Electrónica, TecNM/ITs de Irapuato,Silao-Irapuato km 12.5 El Copal, C.P. 36821 Irapuato, Gto. maría.hh@irapuato.tecnm.mx, marcos.va@irapuato.tecnm.mx
[2]Facultad de Ingeniería, Universidad Autónoma de Querétaro (UAQ) Campus San Juan del Río, Avenida Río Moctezuma número 249, colonia San Cayetano, C.P. 76807. carlos.marinquez@uaq.mx
[3]Óptica no lineal y Procesamiento de Señales, Ingeniería Robótica, Universidad Politécnica de Guanajuato, Comunidad Juan Alonso, Cortazar C.P. 38483, Guanajuato, Mexico. abarrientos@upgto.edu.mx, abarrientos@upgto.edu.mx

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Introduction

Currently, Precision Agriculture (PA) involves the integration of monitoring technologies, sensors, control systems, and data analysis tools with the aim of optimizing crop management in real time. Its goal is to adapt agricultural practices to the specific needs of plants and environmental conditions, enabling a more efficient use of resources such as water, fertilizers, and energy while improving productivity and reducing environmental impact (Soussi *et al*., 2024). Within this context, artificial lighting has become an essential component of controlled-environment agriculture. In particular, light-emitting diode (LED) technology has emerged as an efficient alternative due to its low energy consumption, long operational lifetime, reduced heat generation, and capability to regulate light intensity and spectral composition according to crop requirements (Lozano-Castellanos *et al*., 2025).

Within plant breeding, plant phenotyping is a discipline focused on monitoring and characterizing crops by measuring and analyzing the observable characteristics of plants. Among the most commonly used phenotypic variables are size, shape, color, plant architecture, and leaf area (LA), all of which reflect the crop's physiological status and development. Figure 1 shows the different phenological stages of the bean crop (Phaseolus vulgaris), which include germination, emergence, vegetative growth, flowering, fruit set, maturation, and harvest. During these stages, morphological changes occur that can be quantified using variables such as AF, plant cover, and canopy architecture (Bautista Lozada *et al*., 2012; Correa *et al*., 2019).



Figure 1. Phenological stages of bean crop development.
Source: Authors' own elaboration.

Leaf area is considered one of the most important indicators for assessing plant growth and vigor, as it is directly related to photosynthetic capacity, solar radiation absorption, and biomass accumulation. Traditionally, leaf area is determined using manual or destructive methods, in which leaves are traced onto a reference surface and their area is then calculated using geometric or planimetric techniques.Figure 2 shows an example of this procedure. Although these methods provide acceptable measurements, they have limitations related to processing time, human intervention, and the difficulty of conducting continuous assessments of the same plant (Pentón *et al*., 2006).

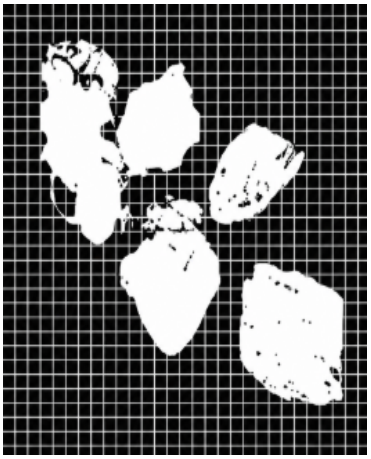


Figure 2. Traditional leaf area determination method.
Source: Authors' own elaboration.

Given these limitations, computer vision (CV) and digital image processing have emerged as tools of great interest for the non-destructive estimation of phenotypic variables. These technologies make it possible to acquire images of plants and extract quantitative information related to their growth in an automated, rapid, and repeatable manner.A computer vision system generally consists of a digital camera for image acquisition, a lighting system that ensures controlled lighting conditions, a shielding structure to minimize external disturbances, and a processing unit responsible for executing the analysis and feature extraction algorithms (Akhtar *et al*., 2024).

At the same time, artificial intelligence techniques have enabled the development of decision-support tools capable of interpreting information acquired from sensors and imaging systems. Among these techniques, fuzzy logic, originally introduced by Zadeh and further developed in fuzzy systems theory, has proven to be particularly suitable for modeling biological systems characterized by uncertainty and nonlinear behavior (Zadeh *et al*., 1996). By using linguistic variables and IF-THEN rules, fuzzy logic facilitates the representation of expert knowledge and provides an effective framework for decision-making in complex environments. Consequently, fuzzy inference systems have been successfully applied in monitoring, classification, and control tasks within agricultural applications. (Correa *et al*., 2019) demonstrated the potential of fuzzy logic for classifying the developmental stages of bean plants, highlighting its ability to represent biological variability and imprecise knowledge.

Various studies have demonstrated the potential of LED lighting and intelligent technologies in controlled-environment agriculture. (Aguirre Becerra, 2020) evaluated the effect of a supplemental LED lighting system on the growth and production of secondary metabolites in tomato seedlings, highlighting the influence of artificial radiation on plant development. Furthermore, (Ahn *et al*., 2017) developed a multi-sensor-based LED lighting system with power control, achieving improvements in energy efficiency during plant cultivation. In the field of artificial intelligence applied to agriculture, (Correa *et al*., 2019) proposed a classification scheme for bean plant development using fuzzy logic, demonstrating the capability of this technique to model the variability inherent in biological processes. Likewise, (Cárdenas León *et al*., 2016) reported the implementation of fuzzy systems on low-cost embedded platforms, demonstrating their feasibility for real-time control applications. Meanwhile, (Herrera Hernández *et al., 2*025) employed computer vision

techniques for bean plant phenotyping through the extraction of morphological variables associated with plant growth and development.

Despite the advances reported in the literature, there are only a limited number of studies focused on the integration of computer vision techniques for estimating leaf area and diffuse control strategies aimed at the dynamic regulation of LED lighting systems.In particular, using leaf area as an indicator of growth status to automatically adjust light intensity represents a promising alternative for improving energy efficiency and providing suitable conditions for crop development.Therefore, this paper proposes a fuzzy control strategy for regulating an LED lighting system, using the leaf area estimated through digital image processing as the input variable.Light intensity is adjusted using a commercial LDH-45A-350W controller, allowing lighting conditions to be adapted based on observed plant growth. The goal is to establish a methodology that contributes to the automation of controlled agricultural environments through the integration of computer vision, plant phenotyping, and fuzzy logic.

Methodology

The methodology developed consisted of the design and integration of an intelligent system for the adaptive control of LED lighting in crops. The system consists of three main stages: image acquisition, digital image processing to estimate leaf area, and fuzzy control of the light output applied to the LED array.

Image capture

The images were captured using an Intel RealSense D435 camera, with a depth resolution of up to 1280 × 720 pixels at 90 frames per second (fps). The camera was mounted in a position relative to the floor plane, as shown in Figure 3. A white polycarbonate frame measuring 0.40 m × 0.40 m × 0.70 m was used. In addition, three 10-watt LEDs were used, arranged in a red-blue-red pattern.

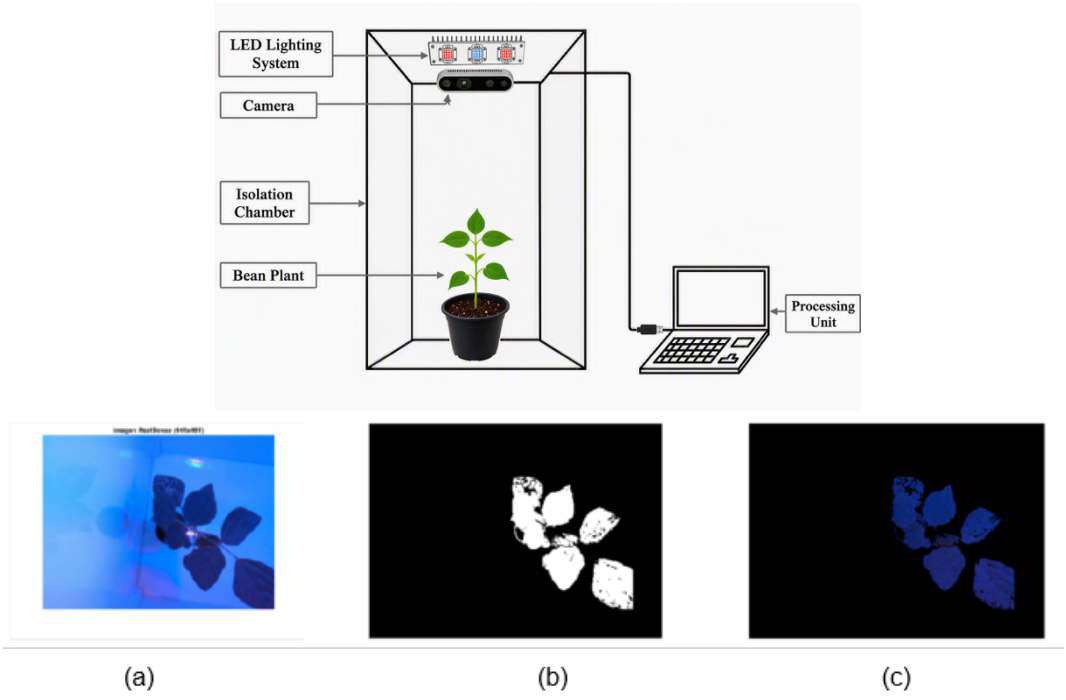


Figure 3. Experimental setup used for image acquisition and plant monitoring. The system consists of an LED lighting system, an Intel RealSense D435 camera, an isolation chamber to minimize external lighting disturbances, a bean plant (Phaseolus vulgaris), and a processing unit responsible for image analysis and leaf area estimation.
Source: Authors' own elaboration.

Digital Image Processing

This step was implemented in MATLAB 2021@ with the goal of extracting the projected leaf area of the plant, as illustrated in Figure 4. Figure 4a shows the image captured in PNG format with a resolution of 640 × 480 pixels. Segmentation was applied to this image using color thresholds of $0 \leq R \leq 0.41$, $0 \leq R \leq 255$, and $50 \leq B \leq 150$.Figure 4b shows the binarized image of the segmentation, and Figure 4c shows the result of the plant segmentation, in which the background has been removed.

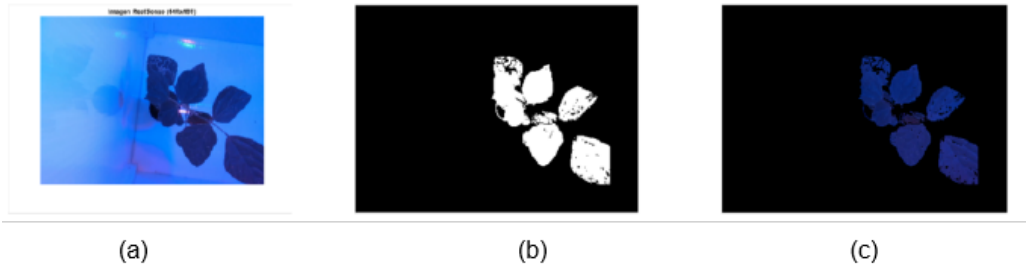


Figure 4. Stages of image processing for the segmentation of Phaseolus vulgaris: a) captured image, b) binarized image, and c) segmentation result. Source: Authors' own elaboration.

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