Monitoring and Analysis of Agricultural Field Parameters in Order to Increase Crop Yield through a Colored Object Tracking Robot, Image Processing, and IOT

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Abstract-Adequately watering plants is a challenging task. Over- and under-watering may harm plants and seeds, as excess or restraint watering reduces crop production and yield. This study presents a method to remotely monitor and efficiently water agricultural fields to increase crop production by utilizing advanced technologies such as internet things, robotics, image processing, and neural networks. Accurate smoothing and image segmentation techniques were employed to study the plants' conditions. Color median, Gaussian, and hybrid median filters were employed to preprocess the data before segmentation and classification. The hybrid median filter and multilevel luminance grading system were employed to increase the quality of the image. The k-means clustering approach was used for image segmentation. The signal-to-noise ratios of the original and recreated images were compared and analyzed.

Keywords-image clustering; hybrid median image smoothing; IoT; robotics; agricultural applications

I. INTRODUCTION

Throughout most of history, farmers used to water plants manually through canals. It is not easy to analyze the amount of manual required drenching, and water the plants to their exact need. Both over- and inadequate watering may lead to the degradation of crop production and reduce crop yield. The current work is a combination of robotics, Internet of Things (IoT), and image processing to reduce the manual effort of the farmers and provide an optimal solution to agricultural field watering. This work was designed for an Arduino board, fitted with different types of sensing and processing units. The motor driver L293D was interfaced with the Arduino board to control a water pump. The robot's movements were controlled using the OpenCV software. The built-in camera captures images and processes them using Gaussian, median, and hybrid median filters to improve their quality. K-means clustering segmentation was used for image segmentation. The objective was to give farmers the ability to analyze remotely the soil conditions and drench the appropriate amount of water depending on soil and plant conditions. This work is more accurate than similar studies. It utilizes three filter stages for image smoothing and k-clustering for image segmentation.

II. RELATED WORK

A prototype fuzzy rule-based irrigation controller that helps farmers save water by providing an ideal watering environment was demonstrated in [1, 2]. Two control units were designed, a wireless sensor and a wireless information processing unit. The wireless sensor unit determined the climate and clay constraints. During summer the water evaporation in soil increases [3, 4]. Based on weather and soil conditions, the sensor detects the water level and sends a signal to the controller. The wireless information processing unit analyzed the information received from the sensor regarding the water level conditions [5, 6]. Based on the obtained parameters, it enables the actuator devices to supply the plants with the required amount of water. The results showed that it reduced the water loss by 27% and increased the yield by 40%. Due to the scarcity of water, different kinds of diseases can be noticed in various plants. In [7, 8], the leaf disease of the guava plant was analyzed using the DCNN framework. In [9, 10] the soil and weather-related features were determined by analyzing various types of soil conditions. Various sensors were used to examine the quality and conditions of various soil types. This study also defined soil suitability for various crops and analyzed the crop production, irrigation, and soil type and condition. Accurate information for the farmers regarding the soil and water conditions was presented in [11, 12]. Various water monitoring and conservation techniques were presented in [13-17].

III. SYSTEM DESIGN

The system model consists of the functional blocks shown in Figure 1. Initially, real-time videos are acquired through the device's built-in camera. Image smoothing is carried out using median, Gaussian, and hybrid median filters. The region of

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interest is captured and image segmentation is performed. After the segmentation, the edges are detected and the contours are identified. Soil moisture, temperature, and humidity are monitored, and finally, plants are appropriately watered by the robot vehicle control.

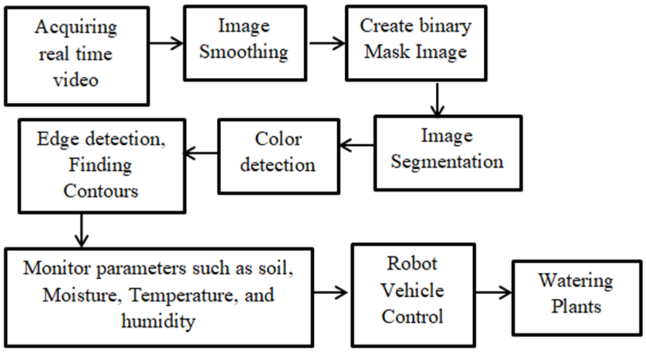

Fig. 1. Block diagram of the proposed work.

A. Image Smoothing

Image filtering and smoothing techniques improve an image's quality by removing noise. Gaussian filter reduces the salt and pepper noise. Noise can be appropriately minimized by keeping the image's edges through median filtering [18]. The brightness of the pixel can be enhanced through median filtering. Figure 2 shows a leaf image before and after applying the median filter. In hybrid-filter, images can be extended symmetrically in horizontal and vertical directions. Additional columns can be added to the left and the right and additional rows can be added at the bottom and the top. Due to this adaptability in image size, this filter is more suitable for fast-moving image smoothing. The block diagram shown in Figure 1 of [19] depicts the hybrid median filter used to recover the image. Impulse noise is added to the input image. Then, the hybrid median filter is applied to the noisy image and effectively eliminates the impulse noise.

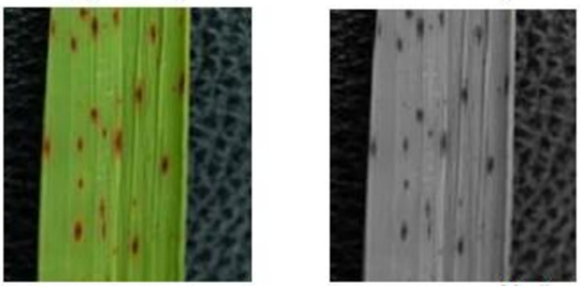

Fig. 2. Images before and after applying the median filter.

In the hybrid median filter, the original pixel values are considered to frame + and *x*-shaped sub-neighborhoods. The first ranking stage is created by considering the + and *x* sub-neighborhoods. The second stage is created by taking the pixels from the first stage and the original pixel. The new pixel value is determined using the median values from the sub-neighborhoods and the original pixel. This filter removes the impulse noise effectively and preserves the edges. The hybrid-median filter performs three-stage operations on pixels to preserve the edges better than the median filter [19].

The calculated median values were:

- Median of horizontal and vertical pixels (MHVP)
- Median of diagonal pixels (MDP)
- Centre pixel (CP)

For an $N \times N$ matrix, considering N=5, the output pixel is the median of {MHVP, MDP, CP}.

Noise is removed using a Gaussian filter. Gaussian smoothing has a similar effect to the median filter in smoothing a picture. The standard deviation determines the degree of smoothing as shown in (1) and (2). Low-pass filtering suppresses high-frequency noise while maintaining the low-frequency elements of an image. The Gaussian filter output is shown in Figure 3.

$$G(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}} \quad (1)$$

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/(2\sigma^2)} \quad (2)$$

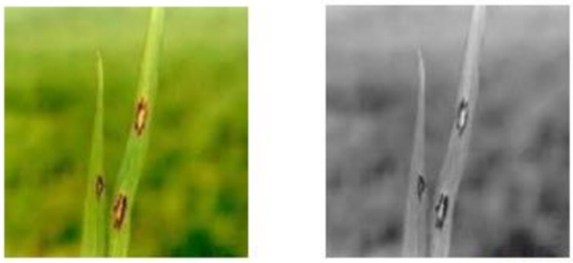

Fig. 3. Image before and after applying the Gaussian filter.

B. Creating Binary Mask Image

The pixels in the Region of Interest (ROI) are set to logic 1 and the remaining pixels of the image are set to logic 0.

C. Image Thresholding and K-means Clustering Segmentation

Segmentation of a captured image is the process of breaking it down into its constituent parts using edge detection, threshold processing, areas-based segmentation, and other techniques. A simple picture segmentation approach is image thresholding. This approach divides foreground from background pixels when converting a greyscale or color image to a binary. The threshold values are compared with the pixel values. Logic 0 is set for the pixels which exceed the cut-off value. If the pixel value falls below the cut-off, then it is set as the logic high value. The k-means unsupervised clustering algorithm was used to classify the dataset.

The following steps define the k-Means set of rules. Figure 4 shows the flowchart representation of the k-means clustering algorithm.

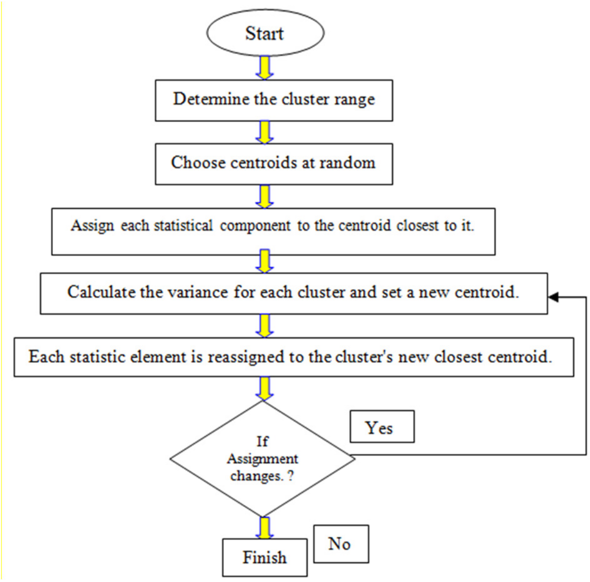

Fig. 4. Flow chart showing the k-means algorithm

D. Color Detection, Extraction, and Grid Formation

Color is extremely important in image processing. Each image made up of an $M \times N$ pixel array is split into M rows and N columns. The red, green, and blue values of each pixel are unique. The RGB colors are identified using thresholds. The intended color of the image is identified using the color recognition process. Figure 5 shows grid formation and robot vehicle control. The user controls the motion of the robot by creating a 3×3 grid matrix. The robot's movement in different directions such as right, left, top, and bottom is controlled by sending commands.

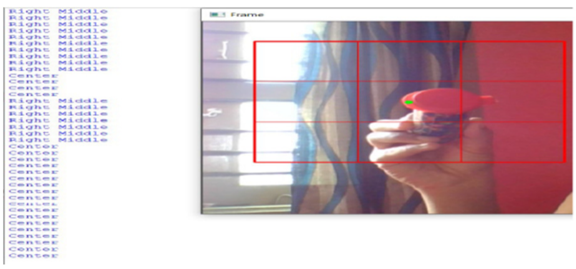

Fig. 5. Color detection, extraction, grid formation, and robot vehicle control.

E. Edge Detection and Contour Finding

Edge detection and contour finding were conducted using OpenCV and Python. As shown in Figure 6, many dots with the same color are joined to form a curve. The different shapes formed are triangle, rectangle, and square by drawing curves, which joins the subsequent points. The following steps are used to identify the shape:

- Create a grayscale version of the image.
- Make a binary representation of the image.
- Determine the contour.

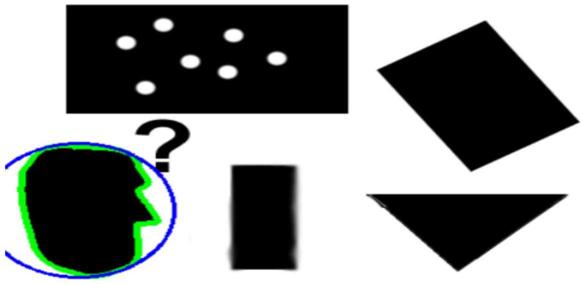

Fig. 6. Edge detection and contour finding.

F. Monitoring Parameters

Parameters such as soil, weather, temperature, humidity, and moisture level of the soil are sensed by different sensors. The sensors capture the data and send them to the data processing units. The image smoothing filter is applied to the captured images and then they are segmented and analyzed properly.

IV. Experiment and Analysis

The camera records a photograph which is a point of reference for the specified user interface. The robot moves forward, backward, left, and right according to the obtained instructions. The movements of the robot are recorded and stored in memory by connecting a WiFi module to the Arduino board. The required object is tracked from the captured image. If the object is red, the robot is moved accordingly in the grid. The block diagram shown in Figure 7 explains the procedure to find the number of clusters.

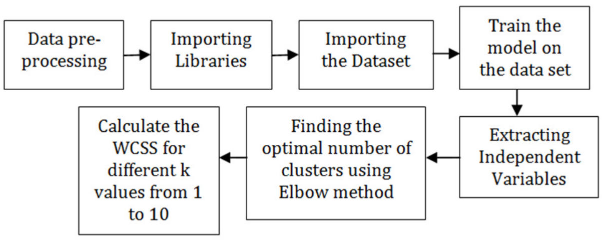

Fig. 7. The process of finding the clusters.

The procedure for the experimental analysis is shown in Figure 9. Figure 8 depicts the number of clusters versus the WCSS list. As shown in the bar graph below, as the number of clusters increases, the sum of squares decreases.

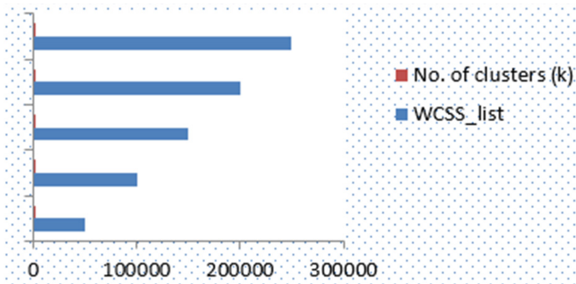

Fig. 8. Number of clusters vs WCSS_list.

The implementation of the prototype model is shown in Figure 10. In this prototype model, the image is captured using the webcam of a laptop. The region of interest is selected and red color is identified. The grid is formed to control the movements of the robot. The chosen parameters are monitored and analyzed.

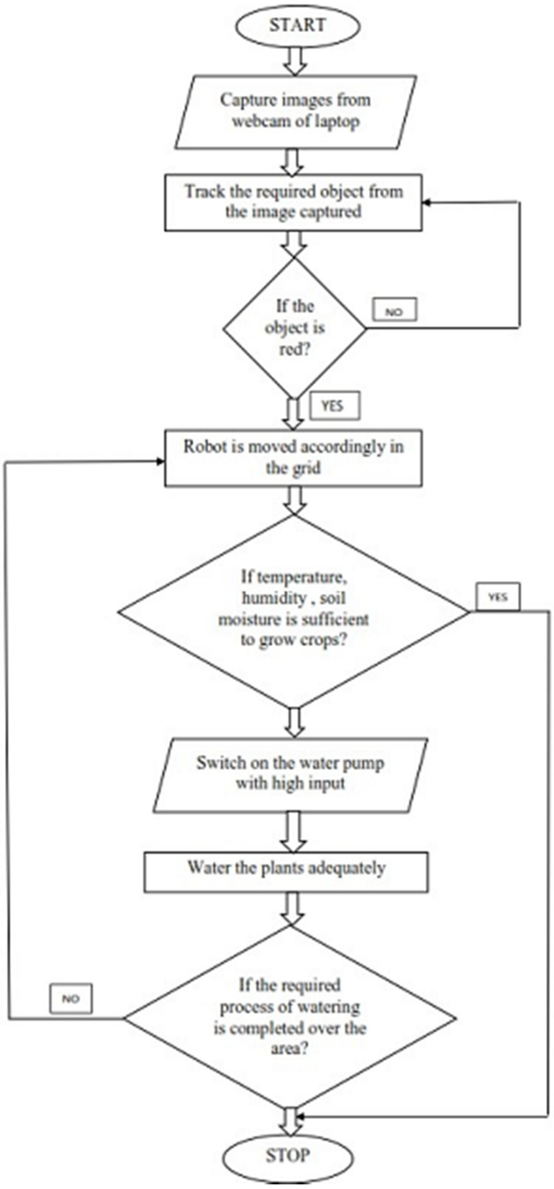

Fig. 9. Flow chart of the experimental procedure.

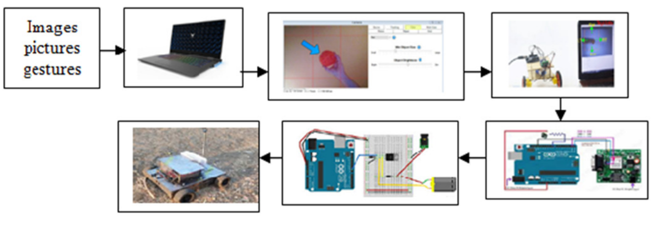

Fig. 10. Prototype implementation.

V. RESULT DISCUSSION AND COMPARISON

The obtained results were analyzed. The captured image signal-to-noise ratio was 30.12dB and the noisy image's SNR was 12.3dB. After passing the noisy image through the median filter, the obtained SNR was 27.7dB. The output of the median filter was applied to the hybrid median smoothing filter. The SNR of the hybrid-median filter was 29.999dB. The SNR of the original and the final processed image were approximately the same. These results were compared with [18]. Table I shows the comparison of SNR of the original with the filtered images. The SNR of the proposed method was 99.59%, whereas the SNR of the previous work was 98.78%. This method improved the SNR value compared to the previous work. The SNR values are graphically represented in Figure 11.

TABLE I. SNR COMPARISON OF ORIGINAL WITH FILTERED IMAGE

Parameters	SNR in dB	
	[18]	Current paper
Captured /original image	20.1408	30.12
Noisy image	13.4343	12.3
Median smoothing Filter	19.1523	27.7
Hybrid Median Filter (HMF) smoothing	19.8964	29.999
Percentage increase	98.78 %	99.59%

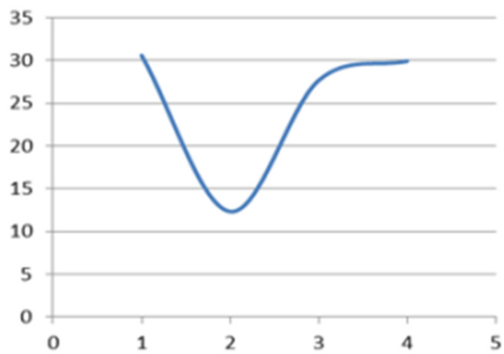

Fig. 11. Signal to noise ratio of the proposed method.

VI. CONCLUSION

An irrigation system using IoT and robotics completes the prototype design. In this work, robotics, IoT, and image processing are utilized. The designed robot is user-friendly and data from different units can be accessed with less delay in real-time. In the image smoothing process, the picture is passed through a median filter, a Gaussian filter, and a hybrid-median filter to remove noise and improve its quality. The raw captured image was filtered by a median filter since it smoothens the image without blurring it. A hybrid-median filter removes effectively the impulse noise, keeps corner features, and does not delete outer boundary lines. The SNR of the captured image was compared with the SNR of the noisy image, median smoothing, and hybrid-median smoothing. The SNR of the captured, noisy, median, and hybrid-median smoothing images was 30.12, 12.3, 27.7, and 29.999 respectively. The SNR of the proposed method was 99.59%, while the SNR of [18] was 98.78%. These results indicate that the proposed method is a feasible alternative for practical applications including picture restoration, medical image despeckling, and image enhancement. The k-means clustering algorithm was employed since it gives a better result in terms of accuracy as compared to traditional methods. The proposed method offers a viable solution to problems associated with agricultural applications.

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