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Autonomous Adjustable Pesticide Spraying Device for Agricultural Application

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Abstract - *This paper presents the development of a smart sensor based environment monitoring system, in remote villages especially for crop fields. Basically, it is difficult to monitor the environment, weather all the time, so we proposed this project in Crop field, to monitor the weather and any environment changes using IOT which having some sensors like Temperature sensor, Moisture sensor, humidity which measures respective parameters throughout the day. And also parameters measured by sensors are sent through IOT. Using measured parameters we can detect and prevent from diseases by spraying pesticides.*

***Key Words*: IoT, Monitoring, Spraying, Image processing, Controlling.**

1. INTRODUCTION

Beginning with the quote "SAVE THE AGRICULTURE", main factor of agriculture is to predict the climatic changes, here we are using IOT for monitoring the weather as well as atmospheric changes throughout the crop field by having several systems in different fields as clients, which is getting reported every time to the server, about the current atmospheric change at that every certain place. So the watering and pesticides can be served based on the conditions of the field. Camera that captured image is processed then identified the disease affected plants and then pesticides to be sprayed.

In this system we are using Raspberry Pi to control the operation of the system. We use small tank in that we add pesticide and place motor to spray. Whenever the sensors detect the diseased plant, the signal is given to Raspberry Pi and it will turn on the motor and start to spray. By making some modification we can use for other applications also.

1.1 FEATURES

1. It can moves in forward direction.
2. It can moves in reverse direction.
3. It can suddenly turn right or left side direction.
4. It can even move sprayer up or down.

1.2 TECHNICAL SPECIFICATION

1. It operates on 9Vdc.
2. Low power consumption of 25 milli ampere current.
3. Operating Voltage of Raspberry Pi module 3Vor 5Vdc.
4. Operating frequency of Raspberry Pi module 400 MHz

1.3 HARDWARE

1. Robot module.
2. Monitoring system.

1.4 SOFTWARE

1.Python Program

2. BLOCK DIAGRAM DESCRIPTION

The block diagram of proposed system is shown below.

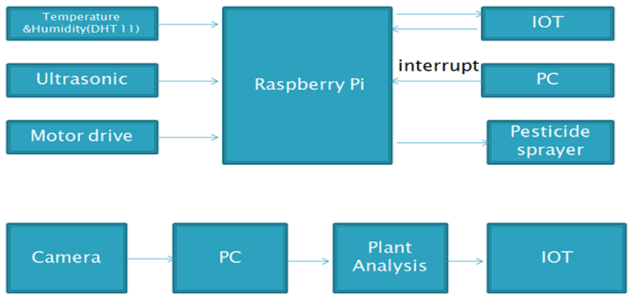

Fig 2.1 Block diagram

This block diagram consist of Camera, Temperature & Humidity (DHT 11) sensor, Ultrasonic sensor, Sprayer, Motor drive (L293D) and Raspberry Pi Kit the description of each block is given in following subsections.

CAMERA:

A Webcam is a video camera that feeds or streams its image in real time to or through a computer to a computer network. When "captured" by the cam, the video stream may be saved, viewed or sent on to other network travelling through systems such as the internet, and wifi as an attachment. When send to remote location, the video stream may be saved, viewed or on sent there. Unlike an IP camera (which connects using Ethernet or wifi), a webcam is generally connected by a USB cable, or similar cable, or built into computer hardware, such as laptops.

TEMPERATURE & HUMIDITY (DHT 11):

The DHT 11 Temperature and Humidity sensor features a calibrated digital signal output. It is integrated with a high performance 8-bit microprocessor. It ensure that high reliability and long term stability. This sensor includes a resistive element and a sensor for wet NTC temperature measuring devices. It has excellent quality, fast response, anti-interference ability and high performance.

Each DHT 11 sensor features extremely accurate calibration of humidity chamber. The calibration coefficients stored in the OTP program memory, internal sensors detect signals in the process, and we should call these calibration coefficients. The single wire serial interface system integrated to become quick and easy. In Small size, low power, signal transmission distance up to 20 meters, enabling a variety of applications and even the most demanding ones. The product is 3-pin single row pin package. It has supply voltage of 5V, Temperature range is 0-50 C and Humidity ranges from 20-90% RH and it has digital interface.

ULTRASONIC SENSOR:

The Ultrasonic sensors measure distance by using ultrasonic waves. The sensor head emits an ultrasonic wave and receives the waves reflected back from the target. Ultrasonic sensors measure the distance to the target by measuring the time between the emission and reception.

An optical sensor has a transmitter and receiver, whereas ultrasonic sensor uses a single ultrasonic element for both emission and reception. In a reflective model ultrasonic sensor, a single oscillator emits and receives ultrasonic waves alternatively. This enables miniaturization of the sensor head.

The distance can be calculated with the formula:

$$\text{Distance } L=1/2 * T * C$$

Where L is the distance, T is the time between emission and reception, C is the sonic speed. (The value is multiplied by ½ because T is the time for go and return distance). It has features such as Transparent object detectable, Resistance to mist and dust, Complex shaped objects detectable.

SPRAYER:

Spray module consists of a spray head, pumps, relays, Servos, screw adjustable rod and DC machine. An ordinary DC motor using L293D high-power motor drive circuit. Sprayer is mounted in a vertical adjustable rod to the driven by the DC motor to rotate the screw may be moved up and down to control the spray platform.

MOTOR DRIVE L293D:

L293D is a typical motor driver or motor driver IC which allows DC motor to drive on either direction. L293D is a 16-pin IC which can control a set of two DC motors simultaneously in any direction. It means that you can control two DC motor with a single L293D IC. Dual H-bridge motor drive integrated circuit(IC).

The L293D can drive small and quiet big motors as well, check the voltage specification. There are 4 input pins for l293d, pin 2, 7 on the left and pin 15, 10 on the right side of IC. Left input pins will regulate the rotation of motor connected across left side and right input for motor on the right hand side. The motors are rotated on the basis of the inputs provided across the input pins as LOGIC 0 or LOGIC 1.

VCC is the voltage that it needs for its own internal operation 5v; l293d will not use this voltage for driving the motor. For driving the motors it has a separate provision to provide motor supply VSS (V supply). L293D will use this to drive the motor. It means if you want to operate a motor at 9v then you need to provide a supply of 9v across VSS motor supply.

The maximum voltage for VSS motor supply is 36v. It can supply a max current of 600mA per channel. Since it can drive motor up to 36v hence you can drive pretty big motors with this l293d. VCC pin 16 is the voltage for its own internal operation. The maximum voltage ranges from 5v and upto 36v.

RASPBERRY PI KIT:

Raspberry pi board is a miniature marvel, packing considerable computing power into a footprint no larger than a credit card. It's capable of some amazing things, but there are a few things you're going to need to know before you plunge head-first into the bramble patch.

The Raspberry Pi Compute Module (CM1), Compute Module 3 (CM3) and Compute Module 3 Lite (CM3L) are DDR2-SODIMM-mechanically-compatible System on Modules (SoMs) containing processor, memory, eMMC Flash (for CM1 and CM3) and supporting power circuitry. These modules allow a designer to leverage the Raspberry Pi hardware and software stack in their own custom systems and form factors. In addition these module have extra IO interfaces over and above what is available on the Raspberry Pi model A/B boards opening up more options for the designer. The CM1 contains a BCM2835 processor (as used on the original Raspberry Pi and Raspberry Pi B+ models), 512MByte LPDDR2 RAM and 4Gbytes eMMC Flash. The CM3 contains a BCM2837 processor (as used on the Raspberry Pi 3), 1Gbyte LPDDR2 RAM and 4Gbytes eMMC Flash. Finally the CM3L product is the same as CM3 except the eMMC Flash is not suit, and the SD/eMMC interface pins are available for the user to connect their own SD/eMMC device. Note that the BCM2837 processor is an evolution of the BCM2835 processor. The only real differences are that the BCM2837 can address more RAM (up to 1Gbyte) and the ARM CPU complex has been upgraded from a single core ARM11 in BCM2835 to a Quad core Cortex A53 with dedicated 512Kbyte L2 cache in BCM2837. All IO interfaces and peripherals stay the same and hence the two chips are largely software and hardware compatible. The pin out of

CM1 and CM3 are identical. Apart from the CPU upgrade and increase in RAM the other significant hardware differences to be aware of are that CM3 has grown from 30mm to 31mm in height, the VBAT supply can now draw significantly more power under heavy CPU load, and the HDMI HPD N 1V8 (GPIO46 1V8 on CM1) and EMMC EN N 1V8 (GPIO47 1V8 on CM1) are now driven from an IO expander rather than the processor. If a designer of a CM1 product has a suitably specified VBAT, can accommodate the extra 1mm module height increase and has followed the design rules with respect to GPIO46 1V8 and GPIO47 1V8 then a CM3 should work in a board designed for a CM1.

It is low in cost, reliable, low power consumption.
Operating voltage is 3Vdc or 5Vdc.

3. METHODOLOGY AND TESTING

Digital Image:

A digital remotely sensed image is typically composed of picture elements (pixels) located at the intersection of each row i and column j in each K bands of imagery. Associated with each pixel is a number known as Digital Number (DN) or Brightness Value (BV) that depicts the average radiance of a relatively small area within a scene. A smaller number indicates low average radiance from the area and the high number is an indicator of high radiant properties of the area. The size of this area effects the reproduction of details within the scene. As pixel size is reduced more scene detail is presented in digital representation.

Image Enhancement Techniques:

Image enhancement techniques improve the quality of an image as perceived by a human. These techniques are most useful because many satellite images when examined on a colour display give inadequate information for image interpretation. There is no conscious effort to improve the fidelity of the image with regard to some ideal form of the image. There exists a wide variety of techniques for improving image quality. The contrast stretch, density slicing, edge enhancement, and spatial filtering are the more commonly used techniques. Image enhancement is attempted after the image is corrected for geometric and radiometric distortions. Image enhancement methods are applied separately to each band of a multispectral image. Digital techniques have been found to be most satisfactory than the photographic technique for image enhancement, because of the precision and wide variety of digital processes.

Contrast Enhancement:

Contrast enhancement techniques expand the range of brightness values in an image so that the image can be efficiently displayed in a manner desired by the analyst. The density values in a scene are literally pulled farther apart, that is, expanded over a greater range. The effect is to increase the visual contrast between two areas of different uniform densities. This enables the analyst to discriminate easily between areas initially having a small difference in density.

Linear Contrast Stretch:

This is the simplest contrast stretch algorithm. The grey values in the original image and the modified image follow a linear relation in this algorithm. A density number in the low range of the original histogram is assigned to extremely black and a value at the high end is assigned to extremely white. The remaining pixel values are distributed linearly between these extremes. The features or details that were obscure on the original image will be clear in the contrast stretched image. Linear contrast stretch operation can be represented graphically. To provide optimal contrast and colour variation in colour composites the small range of grey values in each band is stretched to the full brightness range of the output or display unit.

Non-Linear Contrast Enhancement:

In these methods, the input and output data values follow a non-linear transformation. The general form of the non-linear contrast enhancement is defined by $y = f(x)$, where x is the input data value and y is the output data value. The non-linear contrast enhancement techniques have been found to be useful for enhancing the colour contrast between the nearly classes and subclasses of a main class.

A type of non linear contrast stretch involves scaling the input data logarithmically. This enhancement has greatest impact on the brightness values found in the darker part of histogram. It could be reversed to enhance values in brighter part of histogram by scaling the input data using an inverse log function.

Histogram equalization is another non-linear contrast enhancement technique. In this technique, histogram of the original image is redistributed to produce a uniform population density. This is obtained by grouping certain adjacent grey values. Thus the number of grey levels in the enhanced image is less than the number of grey levels in the original image.

Linear Edge Enhancement:

A straightforward method of extracting edges in remotely sensed imagery is the application of a directional first-difference algorithm and approximates the first derivative between two adjacent pixels. The algorithm produces the first difference of the image input in the horizontal, vertical, and diagonal directions.

The Laplacian operator generally highlights point, lines, and edges in the image and suppresses uniform and smoothly varying regions. Human vision physiological research suggests that we see objects in much the same way. Hence, the use of this operation has a more natural look than many of the other edge-enhanced images.

Band ratioing:

Sometimes differences in brightness values from identical surface materials are caused by topographic slope and aspect, shadows, or seasonal changes sunlight illumination angle and intensity. These conditions may hamper the ability of an interpreter or classification algorithm to identify correctly surface materials or land use in a remotely sensed image. Fortunately, ratio transformations of the remotely sensed data can, in certain instances, be applied to reduce the effects of such environmental conditions. In addition to minimizing the effects of environmental factors, ratios may also provide unique information not available in any single band that is useful for discriminating between soils and vegetation.

Training data:

Training fields are areas of known identity delineated on the digital image, usually by specifying the corner points of a rectangular or polygonal area using line and column numbers within the coordinate system of the digital image. The analyst must, of course, know the correct class for each area. Usually the analyst begins by assembling maps and aerial photographs of the area to be classified. Specific training areas are identified for each informational category following the guidelines outlined below. The objective is to identify a set of pixels that accurately represents spectral variation present within each information region

Select the Appropriate Classification Algorithm

Various supervised classification algorithms may be used to assign an unknown pixel to one of a number of classes. The choice of a particular classifier or decision rule depends on the nature of the input data and the desired output. Parametric classification algorithms assume that the observed measurement vectors Xc for each class in each spectral band during the training phase of the supervised classification are Gaussian in nature; that is, they are normally distributed. Nonparametric classification algorithms make no such assumption. Among the most frequently used classification algorithms are the parallelepiped, minimum distance, and maximum likelihood decision rules.

Parallelepiped Classification Algorithm

This is a widely used decision rule based on simple Boolean "and/or" logic. Training data in n spectral bands are used in performing the classification. Brightness values from each pixel of the multispectral imagery are used to produce an n-dimensional mean vector, Mc = (µck1, µc2, µc3, ... µcn) with µck being the mean value of the training data obtained for class c in band k out of m possible classes, as previously defined. Sck is the standard deviation of the training data class c of band k out of m possible classes.

The decision boundaries form an n-dimensional parallelepiped in feature space. If the pixel value lies above the lower threshold and below the high threshold for all n bands evaluated, it is assigned to an unclassified category. Although it is only possible to analyze visually up to three dimensions, as described in the section on computer graphic feature analysis, it is possible to create an n-dimensional parallelepiped for classification purposes.

The parallelepiped algorithm is a computationally efficient method of classifying remote sensor data. Unfortunately, because some parallelepipeds overlap, it is possible that an unknown candidate pixel might satisfy the criteria of more than one class. In such cases it is usually assigned to the first class for which it meets all criteria. A more elegant solution is to take this pixel that can be assigned to more than one class and use a minimum distance to means decision rule to assign it to just one class.

Minimum Distance to Means Classification Algorithm

This decision rule is computationally simple and commonly used. When used properly it can result in classification accuracy comparable to other more computationally intensive algorithms, such as the maximum likelihood algorithm. Like the parallelepiped algorithm, it requires that the user provide the mean vectors for each class in each hand µck from the training data. To perform a minimum distance classification, a program must calculate the distance to each mean vector, µck from each unknown pixel (BVijk). It is possible to calculate this distance using Euclidean distance based on the Pythagorean theorem.

The computation of the Euclidean distance from point to the mean of Class-1 measured in band relies on the equation

Dist = SQRT{ (BVijk - µck) 2 + (BVijl - µcl) 2}

Where µck and µcl represent the mean vectors for class c measured in bands k and l.

Many minimum-distance algorithms let the analyst specify a distance or threshold from the class means beyond which a pixel will not be assigned to a category even though it is nearest to the mean of that category.

Maximum Likelihood Classification Algorithm

The maximum likelihood decision rule assigns each pixel having pattern measurements or features X to the class c whose units are most probable or likely to have given rise to feature vector x. It assumes that the training data statistics for each class in each band are normally distributed, that is, Gaussian. In other words, training data with bi-or trimodal histograms in a single band are not ideal. In such cases, the individual modes probably represent individual classes that should be trained upon individually and labeled as separate classes. This would then produce uni-modal, Gaussian training class statistics that would fulfill the normal distribution requirement.

The Bayes's decision rule is identical to the maximum likelihood decision rule that it does not assume that each class has equal probabilities. A priori probabilities have been used successfully as a way of incorporating the effects of relief and other terrain characteristics in improving classification accuracy. The maximum likelihood and Bayes's classification require many more computations per pixel than either the parallelepiped or minimum-distance classification algorithms. They do not always produce superior results.

Classification Accuracy Assessment

Quantitatively assessing classification accuracy requires the collection of some in situ data or a priori knowledge about some parts of the terrain which can then be compared with the remote sensing derived classification map. Thus to assess classification accuracy it is necessary to compare two classification maps 1) the remote sensing derived map, and 2) assumed true map (in fact it may contain some error). The assumed true map may be derived from in situ investigation or quite often from the interpretation of remotely sensed data obtained at a larger scale or higher resolution.

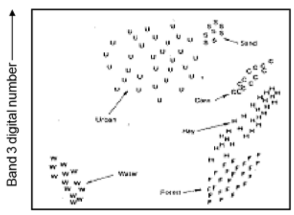

Figure 7a: Pixel observations from selected training sites plotted on scatter diagram

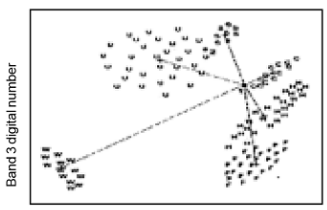

Figure 7b: Minimum Distance to Means Classification strategy

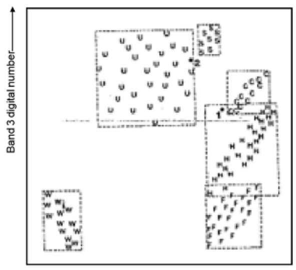

Figure 7c: Parallelepiped classification strategy

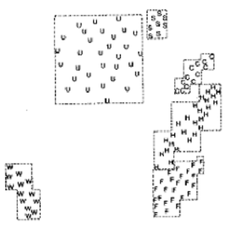

Figure 7d: Stepped parallelepipeds to avoid overlap

Classification Error Matrix

One of the most common means of expressing classification accuracy is the preparation of classification error matrix sometimes called confusion or a contingency table. Error matrices compare on a category by category basis, the relationship between known reference data (ground truth) and the corresponding results of an automated classification. Such matrices are square, with the number of rows and columns equal to the number of categories whose classification accuracy is being assessed. Table 1 is an error matrix, an image analyst has prepared to determine how well a Classification has categorized a representative subset of pixels used in the training process of a supervised classification. This matrix stems from classifying the sampled training set pixels and listing the known cover types used for training (columns) versus the Pixels actually classified into each land cover category by the classifier (rows).

Table 1. Error Matrix resulting from classifying training Set pixels

	W	S	F	U	C	H	Row Total
W	480	0	5	0	0	0	485
S	0	52	0	20	0	0	72
F	0	0	313	40	0	0	353
U	0	16	0	126	0	0	142
C	0	0	0	38	342	79	459
H	0	0	38	24	60	359	481
Column Total	480	68	356	248	402	438	1992

Classification data Training set data (Known cover types) ⟶

Producer's Accuracy	Users Accuracy
W=480/480 = 100%	W= 480/485 = 99%
S = 052/068 = 16%	S = 052/072 = 72%
F = 313/356 = 88%	F = 313/352 = 87%
U =126/241l = 51%	U = 126/147= 99%
C =342/402 = 85%	C = 342/459 = 74%
H = 359/438 = 82%	H = 359/481 = 75%

Overall accuracy = (480 + 52 + 313+ 126+ 342 +359)/1992 = 84%

W, water; S, sand; F, forest; U, urban; C, corn; H, hay

Similarly data can be taken for plant only and image processes is done and train the specific or all kind of plants in module. This data can be stored in database as a reference.

Thus the camera capture image is processed digital by following methodology as mentioned above.

4. WORKING OF AUTONOMOUS PESTICIDE SPRAYER

In this project, whenever our atmospheric condition changes sensors connected to Raspberry Pi sense and monitor weather throughout the day. If temperature becomes low and humidity is more than robot starts to move in crop field. The supply is given to motor by DC battery. According to logic programmed in L293D motor drive give commands to robot (Forward, Backward, Left Turn, Right Turn).When an plant or object is detected by using ultrasonic sensor(within 50cm). If it is detected then it gives trip signal to motor drive and motor gets stop. The Camera connected to Raspberry Pi will capture image and it will undergoing digital image processing. If plant is seem to be affected then this information is shared to L293D, the servomotor connected to L293D will turn on pesticide sprayer and its sprays.

After completion of spraying robot turns and go to next plant and starts image processing. When a plant is not affected by diseases then sprayer will not operate.

The overall setup is shown in figure below:

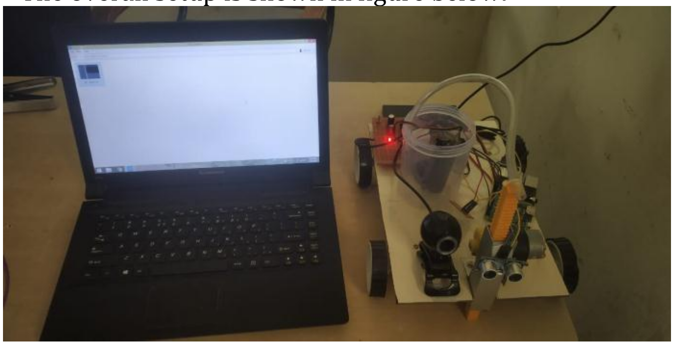

Fig 4.1 Prototype Model

5. CONCLUSION

According to this system, irrigation system becomes more autonomous with quick transmission of data by using IOT. The main advantage in IOT is, even when clients are not in the node network, data will be sent, whenever a client is connected with that node, they can able to see the data which has been sent already. So they can able to analyze the atmospheric change throughout every day and improve the crop production. It also reduces the usage of pesticides upto 30-40%.

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