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Using Mobile Robots To Act As Surveillance In The Crop Field

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ABSTRACT:

The use of robots in the field of agriculture has been widely anticipated. This paper presents the concept of using robots and artificial intelligence for identification of pests and weeds present in the agricultural field. A random image from the agricultural field is taken by using a robot that consists of flash memory. The images taken by the robot are stored in the flash memory and thenare pre-processed using image processing techniques and finally is given as input to the neural network for identification of any types of pests or weeds that is present in that particular image. Back propagation algorithm is used for training the network. The training set is classified into six classes and each class consists of fifty images for training and another 10 images for testing the network. Different types of pests and weeds that affect the rice plantation is taken and categorized into six classes and these data sets are used to train and test the neural network.

INTRODUCTION:

There has been significant improvement in the field of agriculture in the past decades. Due to increase in population, agricultural lands have been compromised to construct industrial buildings and houses. To significantly improve the yield of crops and protecting them against various types of pests and weeds, an efficient machine learning system that is capable of identifying the type of weeds and pests present in the crops is needed. Detecting the foreign bodies at an early stage could improve the yield and protect the crops from withering. Computer vision and neural networks are combined to detect and identify pests and weeds[1]. There are three major processes involved in this: the images are taken from the crop field. The characteristics of each class are defined and required features are extracted from the images. Then, a classification algorithm is implemented which takes the features of the image as input and outputs the correct class that the image belongs.

Neural networks along with logistic regression are used for classification and training of the network.

Back propagation neural networks are one of the most effective types of neural network. A typical back propagation neural network is illustrated in figure: 1a which consists of an input layer, a hidden layer and an output layer. The nodes in the input layer are connected to each and every node in the subsequent layer. The threshold and the weights between the nodes are initialized between -1 and 1. The input to each node is calculated as the sum of product of input of each node in the preceding layer and the weights between the nodes. An activation function is then applied to each node to calculate the output of each node. Sigmoidal activation works well for most classification problem. The input of each node is passed to this sigmoidal activation function and its output is calculated. Once the output is determined at the output layer, the error is calculated between the actual output and the desired output. The error signal for each node in the output layer is calculated and the weights between the nodes in the hidden layer and output layer are adjusted. Then, the error signal for each hidden layer is calculated and is back propagated till the first hidden layer and the weights between each hidden layer nodes are adjusted till the desired output is obtained.

METHODOLOGY:

The proposed work is divided into three stages. They are:

1. Designing a gesture controlled robot.
2. Image acquisition and feature extraction
3. Training and classification

DESIGNING A GESTURE CONTROLLED ROBOT:
ARCHITECTURE:
TRANSMITTER:

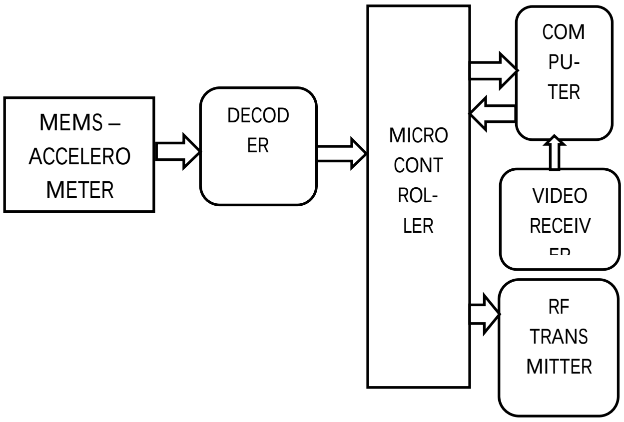

Figure. 1a. Block diagram of transmitter.

The architecture of the gesture controlled robot is shown in figure 1a and 1b. It consists of a transmitter to transmit the gesture signals for the movement of the robot by reading our hand movements and a receiver to receive the gesture signals from the transmitter[2]. Based upon the transmitted hand gesture signal the robot will move accordingly. The robot consists of a wireless camera and a video transmitter to transmit the images to a computer system. The images are then analysed by pre-processing them at first and then extracting the desired features of the image. The extracted features are given as input to the neural network and are tested to check whether the network has been trained successfully[3]. Linear regression is used for classification of the images into different classes.

RECEIVER:

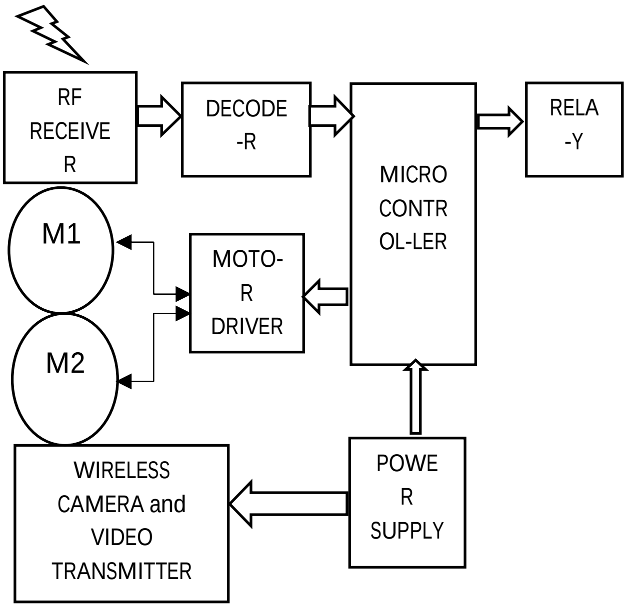

Figure. 1b. Block diagram of receiver.

A. GESTURE MOVEMENTS:

The output of gesture recognition system is to move the robot accordingly. The different types of gesture commands that can be given to the robot are Forward, Backward, Right and Left movement[4]. These gesture commands are generated from the gloves worn by the user which consists of a MEMS accelerometer. The lookup table in the microcontroller has various values stored for each movement Fig. 2. The robot will move according to the values in the microcontroller.

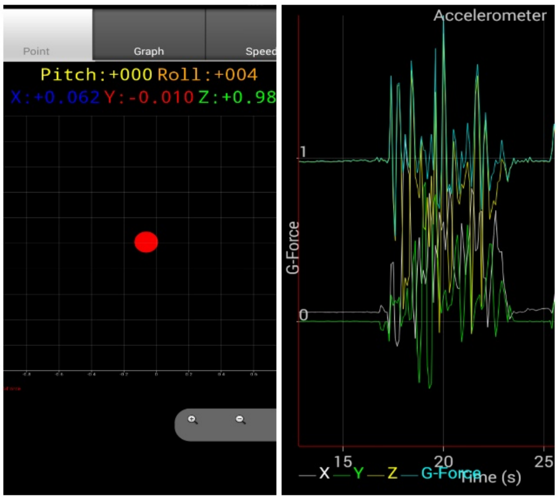

Figure. 2. X, Y, Z Accelerometer Reading.

B. FEEDING LOOKUP TABLE IN MICROCONTROLLER:
Lookup table is where the acceleration values are stored in the microcontroller for which the control signals are generated[5]. The lookup table can be feed by the user to the microcontroller using the embedded c programming concept in MPLAB IDE. Each command should have a separate range of acceleration values to avoid the jamming of control signals.

C. SIGNAL GENERATION IN THE RECEIVER:
The microcontroller moves only after verifying the input signal from the hand gloves[6]. Whenever the hand palm with the accelerometer transmits a signal, the receiver receives the value and compares it in the lookup table. Finally, the microcontroller generates the control signal.

D. RF TRANSMITTER AND RECEIVER:
The radio frequency (RF) range varies between 30 KHz and 300 GHz[7]. In this radio frequency system the digital data is represented as variations in the amplitude of carrier wave Transmission through RF is better than IR (Infra-Red) because RF can travel through larger distance also RF can travel even when there is anobstruction between transmitter and receiver[8]. For long range application only RF transmission is used because it is more strong and reliable than IR transmission.

The RF module comprises of an RF transmitter and RF receiver. The transmitter/receiver pair operates at a frequency of 434 MHz. The RF receiver receives the control signals from RF transmitter[9] and sends it to the micro controller connected with it. The transmission occurs at the rate of 1Kbps to 10 Kbps. The RF module is often used along with a pair of encoder and decoder. The encoder is used for encoding parallel data for transmission similarly the decoder is used for decoding on the receiver side. HT12E-HT12D, HT640-HT648 is commonly used encoder/decoder pair ICs.

E. DC GEAR MOTORS:
A motor is a machine which converts energy into rotating motion. A DC motor is a motor that uses direct electric current as the source of the energy. DC current is the type of electricity provided by batteries. A gear motor is a motor with an attached set of gears driving a secondary drive shaft[10]. The current in the rotor is switched by the commutator. The commutator allows each armature coil to be activated. DC motors is suited for rangingequipment from 12V DC systems in automobiles to conveyor motors[11], both that requires fine speed control for a range of speeds above and below the rated speeds. Motor speed is generally measured in revolution per minute (RPM). Rotating force is called torque and for hobby motors is generally measured in centimetre-grams. Gearing down a motor reduces its RPMs but increases its torque. Conversely gearing up a motor increases its RPMs but decreases its torque.

Gears are generally contained within a housing that protects the gears from interference and which provides a bearing surface for the various gear shafts and drive shafts. The term gear box refers to the entire system of gears, shafts, bearings and housing. When energy is applied to the motor it will spins as fast and hard. A load is attached to the motor to slow down the speed[12]. When the extreme load causes the motor to stop it is known as stalled. A device which detects the rotation of a shaft is called a shaft encoder. By counting rotations for a period of time the motor speed can be determined.

IMAGE ACQUISITION AND FEATURE EXTRACTION:
The images are split into six different classes each containing a set of 50 images each for testing and another 20 for testing[13]. The features of the image are extracted using content based image retrieval (CBIR).

The edges of the image are detected using sobel's edge detection technique. It returns an image with edges detected based on a threshold value and then is filtered using median filtering technique as mentioned in [14]. The image features are extracted using texture based colour co-occurrence method. The Segmentation based Fractal Texture Analysis (SFTA) algorithm is used for texture extraction. This algorithm decomposes the input image into a set of binary images from which fractal dimensions of the resulting regions are computed in order to describe segmented texture patterns [15]. The decomposing of input image is done by using Two-Threshold Binary Decomposition (TTBD) algorithm. The threshold binary decomposition algorithm takes a grayscale image as input and outputs a set of binary image. The first step of TTBD is to compute a set of threshold values. The threshold values is obtained by usingthe input image's gray level distribution information. This is achieved using multi-level Otsu's algorithm. The next step in TTBD is to decompose the input grayscale image into a set of binary images. The set of binary images is obtained by applying two threshold segmentation to the input image using all pairs of contiguous thresholds[16].

The SFTA feature vector consists of the binary images' size, mean gray level and boundaries' fractal dimension. The vector dimensionality is equalto three times the number of binary images acquired by using TTBD. Fractal dimensions are computed using box counting algorithm.

The SFTA feature vector is then used for classification using neural networks.

	1	2	3	4	5
1	1.3595	87.4943	82936	1.4462	118.1130
2	1.3491	86.5886	75986	1.4358	117.4689
3	1.3579	87.6811	84628	1.4458	118.1233
4	1.3320	86.1314	66627	1.4323	117.2407
5	1.3567	87.1285	81650	1.4375	117.6594
6	1.3422	87.1767	77990	1.4382	117.8336
7	1.3442	86.7841	75448	1.4372	117.4429
8	1.3197	85.3366	62078	1.4201	116.5267
9	1.3475	86.2341	77704	1.4467	117.6555
10	1.3114	85.0674	56848	1.4163	116.4066
11	1.3439	86.4830	72306	1.4403	117.9734
12	1.3238	86.3234	66769	1.4280	117.0403

Fig. 2. 1 Dataset for images

TRAINING AND CLASSIFICATION:

The back propagation algorithm is implemented by using two hidden layers of 10 neurons each. The output layer consists of 5 neurons. The value 1 in any one of the column indicates a separate class. For example, 00001 indicates class 1, 00010 indicates class 2 and son on. The input layer consists of 10 neurons depending on the feature extraction method and the number of features extracted[17]. A momentum was applied to the network to converge to the global minima. Finally a test data set is used to test the classification accuracy of the trained the network.

Matlab is used for the implementation of neural networks and image processing. The weights between the nodes are initialized to a random value between -1 and 1, the inputs to the input layer nodes are specified and the training is executed. The sigmoid activation function is used for activating the nodes in the hidden and output layers. The errors in the nodes are calculated and the error signal value is back propagated to re-calculate the weights. There are different problems associated when designing a neural network like overall classification accuracy and individual classification accuracy. The default value of the learning rate in MATLAB is 0. 050 and for momentum, it is 0. 95. The network is trained and the resulting results are tabulated.

CONCLUSION:

This paper describes that how a simple robot could surveillance the agricultural field for detecting the pests. The microcontroller captures the image and this image is sent to the system and is processed using image processing. SFTA algorithm is used to extract the features from the given image and this vector is used to train the backpropagation neural network. The system correctly classifies to an accuracy of 96%.

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