Chapter 13
Design of an Agribusiness Innovative and Autonomous Robot System for Chemical Weed Control for Staple Food Crops Production in Sub-Saharan Africa

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ABSTRACT

Agriculture and agribusinesses suffer from many challenges, despite their significance to global economic growth. One of the challenges is the lack of appropriate technology to drive the industry to the next level of development. This technological gap contributes to reduced yield and profit without a reduction in manual labour, cost, and stress. Robotics have been explored to boost agricultural production and improve agribusiness productivity. Several weed control robots have been developed for research and field uses, but these systems are not suitable for weed control in large commercial farms or lack control schemes for navigation and weed control. This study presents the design of an autonomous robot system for chemical weed control. The system uses control theory, artificial intelligence, and image processing to navigate a farm environment, identify weeds, and apply herbicide where necessary. Upon implementation and adoption, this system would increase agricultural productivity with minimal human input, thereby leading to an increase in revenue and profit for agribusinesses.

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INTRODUCTION

The concept of Agribusiness is the sum of all operations involved in the production and distribution of farm produce, farm production operations, storage, processing, and distribution of farm commodities (Ikenwa, Sulaimon, & Kuye, 2017). It is a generic term for different businesses involved in the production and along the value chain of an agricultural commodity which includes but not limited to subsistence and mechanized farming, the supply of seeds, fertilizers, manure, chemicals, machinery, marketing, and financing of the agricultural industry (Munonye & Esiobu, 2017).

In recent times, there has been increased pressure on the agricultural industry and agribusinesses to operate and deliver more efficiently and effectively due to an increase in the world's population (Munonye & Esiobu, 2017). Agribusiness has the capacity and potential to provide increased employment, poverty reduction, higher income, and food security (Tersoo, 2013). Nevertheless, given the sector's ability to revolutionize the sub-Saharan African region's agricultural commodity production, agribusiness suffers from numerous constraints. The challenges associated with agribusinesses in Sub-Saharan Africa include poor policy articulation, inadequate working capital, lack of suitable technology, and inadequate agricultural infrastructure (Munonye & Esiobu, 2017). These challenges limit the revenue and profits generated from the industry.

Productivity in agriculture and agribusinesses can be increased by appropriate, accurate, and usable information and knowledge. Agricultural information interacts with agricultural productivity in a variety of ways, influencing it. It helps inform land, labor, livestock, capital, and management decisions. Consequently, the processing of agricultural information (through extension facilities, research, and education programs) is most mostly handled by agricultural organizations that build information systems to disseminate knowledge to farmers (Demiryurek, 2008). This knowledge enables the farmers to make informed decisions to take advantage of market incentives and handle constant improvements in their production processes. Information obtained from farms can be collected using systems that employ the concepts of Precision Agriculture, Artificial Intelligence, and Robotics. These devices rely on the use of sensors to obtain environmental data which can then be analyzed using a variety of software tools.

Globally, there has been an increase in the application of robotic systems to automate agriculture-based problems (Roldán et al., 2018). According to the United Kingdom Robotics and Autonomous Systems (UK-RAS) Network, robotics and autonomous systems will transform numerous global industries including the agricultural sector through the development of technologies aimed at maximizing profit and increasing yield (UK RAS Network, 2018). In addition, advancements in precision agriculture have resulted in the utilization of intelligent machines to minimize human involvement while increasing agricultural output. The development of robots and their application in agriculture has increased leading to the exploration of possibilities to adapt rational mobile robot solutions based on behavioral approaches (Pedersen, Fountas, & Blackmore, 2008).

A major problem faced by farmers is the prevalence of weeds. A weed is any unwanted crop that grows in an unwanted area. Weeds reduce not only yield but also the confidence of farmers by creating a poor return on investment. Weeds also result in higher production costs and lead to seedling contamination. Manual weed control with hand-held hoes and manual application of herbicides with knapsack sprayer is labor-intensive and exhausting. This fatigue-inducing weed control approach discourages a lot of people from moving into crop farming (Olaniyi, Daniya, Kolo, Bala, & Olanrewaju, 2020). In a quest to improve agricultural productivity, attempts have been made to introduce robotic systems for weed management. However, these systems have drawbacks such as inadequacy for vast outdoor fields, lack of control schemes, lack of intelligent technology, and requirement of human involvement. The need for a device capable of detecting and managing weeds in farmland exists because of these shortcomings. This system requires minimal human intervention, large farmlands, incorporates control and smart operation schemes.

In this study, the design process of an autonomous robotic system for chemical weed control is presented. This system utilizes precision agricultural and robotic concepts to carry out effective weed management. This system is expected to increase agricultural output, for high investment returns and increased profits. The implementation of this design and subsequent adoption of this system by farmers in sub-Saharan Africa has the potential to improve the development of a crop commodity along the agricultural value chain and agribusiness sectors.

PROBLEMS OF AGRICULTURE IN NIGERIA

Nigeria is the largest economy in West Africa and the second-largest in sub-Saharan Africa. Nigeria is large and vast with 68 million hectares of it being arable land, 12.6 million hectares of freshwater resources, and an ecological diversity that provides the necessary resources for the production and cultivation of a wide variety of crops (Ewetan, Adebisi, & Emmanuel, 2017). The Nigerian economy has been described as an "Agrarian Economy", where agriculture plays a vital role in the country's social and economic development (Anigbogu, Agbasi, & Okoli, 2015). Agriculture contributes about a quarter of the total nominal Gross Domestic Product (GDP) of Nigeria. This number is, however, lower than the sector's previous contribution because agricultural production has declined over the years. This decline has led to many major food products being imported into Nigeria that can be grown locally.

The decline of agricultural production in Nigeria has been attributed to the over-dependence of the country's economy on crude oil and the increase in population without a corresponding increase in agricultural products (Anigbogu et al., 2015; Nwankpa, 2017). Despite efforts by the government to improve agricultural production by introducing schemes and programs such as Operation Feed the Nation (OFN), Green Revolution, and National Food Acceleration Production Programme (NAFPP), agricultural output has not improved significantly. The reasons are due to policy inconsistencies, corruption, and mismanagement (Nwankpa, 2017).

Additional factors that affect the development of agriculture in the region are the absence of good agricultural infrastructure, market problems, unstable prices, and poverty, especially in rural areas (Ufiobor, 2017). In addition, the system's lack of innovativeness arising from unstimulated drivers of agricultural development is another aspect that adversely affects agricultural production. These factors lead to low returns on investment, mismanagement, wastage of produce, and inability to obtain suitable agricultural inputs such as fertilizers, herbicides, insecticides among others.

The implementation of smart and intelligent technologies in agriculture can optimize operations involving crop care, harvesting, seeding, and yield improvement. However, the application of these concepts in the Nigerian agricultural sector is hindered by factors such as lack of capital and inadequate facilities. For instance, a lack of capital involved in the deployment of smart technologies hampers the adoption of automation in farms. Even if the equipment is acquired, the lack of electricity access for the majority of the country's population impedes the use of mechanized and smart farming equipment. In addition, the lack of adequate knowledge of precision farming technologies is prevalent to the majority of the farmers in Nigeria are in rural areas. These farmers, due to their illiteracy, are also unskilled in the abilities required to deploy the technology (Elijah, Babale, & Orakwue, 2017).

Weeds: The Farmers' Battle

In crop production, the prevalence of weeds has been and continues to be a challenge to farmers in the sector. The effects are not only conspicuous in the growth of the crops being cultivated but also in the production yield and capability of the farmers. In sub-Saharan Africa, weeds result in a rice loss of about 2.2 million tons, the losses which are estimated at about $1.45 billion (Olaniyi, Daniya, Abdullahi, Bala, & Olanrewaju, 2019).In Imoloame & Omolaiye (2017), a yield loss of about 51 to 100% was reported to have been sustained due to weed competition in maize farms in Nigeria. In the long run, more efforts are being exerted to reduce the negative effects of weeds on the farm which increases the production cost. This process often dampens the morale of the farmers due to the reduced profit realized at the end (Olaniyi et al., 2019).

In practice, there exist different approaches in controlling weeds on the farm. One such method is manual weed control. In this approach, the use of hoes and other tools are being employed to manually and physically remove the weeds from the farm. The applications of various herbicides through spraying and direct application (where spraying may be difficult) are also adopted. The characteristic features of this practice are the extent of manpower, fatigue and cost involved.

Hence, in order to solve these identified challenges and make farming of crops more lucrative, there is a need to develop a more comprehensive and all-encompassing system for the identification and control of weeds in farmlands. This is with the view of making the practice more lucrative in terms of the return of investment, yield of production and reduction in the amount of stress involved.

Precision Agriculture for Weed Control

Precision Agriculture (PA) is a theory which is based on the observation, measurement, and response to variability in crop fields or aspects of livestock management.(Beluhova-Uzunova & Dunchev, 2019). This process involves the application of inputs only when and where it is required. The PA has become the third stage of the agricultural revolution, second to mechanization and the green revolution. The concept aims at increasing and maintaining the sustainability of crop production and animal rearing by the applications of Artificial Intelligence, Internet of Things, Big Data, and Robotics (Saiz-Rubio & Rovira-Más, 2020).

The PA underscores the fact that increased agricultural output can be obtained by understanding variability within a crop field. The objective is not to obtain the same outputs or yield all around the farm but to analyze the environment and distribute various inputs based on site-specificity. This process has the potential to result in a high return on investment and maximize benefits from farming such as increasing productivity, improving profitability, and reducing wastage (Banu, 2015). The size of arable farmlands in Nigeria has grown over time due to increasing demand and population (Abdullahi & Sheriff, 2017). It has become almost impossible for farmers to maintain knowledge of field conditions due to the variability associated with the environment. The PA gives farmers the opportunity to simplify and automate data acquisition and analysis, thereby resulting in quick, intelligent, and in some cases, automated decision making.

In the past, the predominant small-scale farms allowed farmers to observe the spatial variability of their farmlands and apply inputs accordingly. However, the advent of mechanized agriculture led to an increase in the size of farms with a uniform application of inputs across the land. The PA bridges the gap between the two practices by obtaining information about the farmland and applying inputs based on data analysis with the aid of sensors and actuators. Farm operations such as herbicide application, fertilizer application, and irrigation can be carried out intelligently, thereby allowing the farmers to obtain high yields, minimize inputs, reduce wastage, and optimize profits (Beluhova-Uzunova & Dunchev, 2019).

In the aspect of chemical weed control, PA plays an important role by precisely managing production factors such as herbicides to increase yield and efficiency (Hakkim, Joseph, Gokul, & Mufeedha, 2016). In Rodenburg et al., (2019), it was reported that a frequently observed complaint by farmers regarding the use of herbicides is the high cost involved. In addition, it was observed that the majority of farmers in Sub-Saharan Africa use herbicides complementarily to hand-weeding (Rodenburg et al., 2019). The PA can successfully be implemented to minimize wastage of herbicides resulting from a uniform application across the farm (even in areas that do not require herbicide). Furthermore, PA reduces the need for frequent herbicide usage, which may have negative effects on the environment, human health, and crops.

Review of Literature

Autonomous robots have been implemented for a wide range of farm operations. In Belgium, an autonomous tractor has been used in uneven and inconsistent terrain for farm operations. Depending on the type of terrain, the user calibrates the robot to prevent the robot from falling off its desired path. Additionally, Vitirover is a robot designed for use in New Zealand that can detect and cut weeds in a grape field. Hortibot, in addition, is an autonomous robot developed and used in Denmark. This device is used for spraying or laser removal of weeds. However, the system and the technique it employs are very costly and can hinder farmers' adoption (Sujaritha, Lakshminarasimhan, Fernandez, & Chandran, 2016).

In the aspect of automatic weed detection and control, several works exist in literature. Mohan et al., (2016) developed an automatic weed detection system and smart herbicide sprayer robot for maize production in India. In this system, the image processing technique is used to detect weeds and spray herbicides accordingly. However, there is no technique to control the amount of herbicide sprayed. Similarly, automatic detection and smart herbicide sprayer robot were developed by Aravind, Daman, & Kariyappa, (2015). The system detects weed using image processing and sprays herbicide accordingly. However, due to the size of the system, it is not suitable for large and commercial farm operations.

A weed control system for precision agriculture based on computer vision was proposed by Arakeri, Vijaya Kumar, Barsaiya, & Sairam, (2017). The system captured real-time images from a farm and uploaded them to a remote server to be analyzed by a machine-learning algorithm. Based on the output of the algorithm, the herbicide is then sprayed accordingly. Although the system exhibited an accuracy of weed detection of 96.83%, the system could not autonomously navigate the farm. In addition, no control scheme was incorporated to limit the amount of herbicide sprayed.

In Nielsen, Andersen, Pedersen, Bak, & Nielsen, (2002), the control of an autonomous vehicle for weed and crop registration in precision agriculture was presented. The system was capable of following a reference path autonomously due to the control scheme implemented. However, the system lacked any feature for weed identification, and the navigation of the robot was based on a predefined path, which may not be suitable for dynamic environments. Similarly, Hameed, Cour-Harbo, and Hansen, (2014) presented a task and motion planning technique using a team of autonomous vehicles for selective weed control. The system obtained satellite images using unmanned helicopters and transmitted them to the ground vehicles. This enabled the ground vehicle to visit infested areas for weed treatment. Despite showing satisfactory performance in path tracking, the system lacked an image-processing algorithm for autonomous weed detection or a control scheme for weed control.

Kulkarni & Deshmukh (2013) developed an advanced robotic weed control system. The system employed the use of a color sensor and an infrared sensor to identify weeds. The system, however, provided no technique for weed control, and color alone is not a suitable criterion for identifying weeds. In Bak & Jakobsen, (2004), an agricultural robotic platform with four-wheel steering for weed detection was developed. The work focused on the navigation of the robotic device within a field. Although the vehicle was capable of following a predefined path within a field, no information was provided on its weed detection capabilities.

Kounalakis, Malinowski, Chelini, Triantafyllidis, & Nalpantidis, (2018) developed a robotic system which employed deep learning for visual recognition and detection of weeds in grasslands. The system used convolutional neural networks to identify weeds while keeping a low false-positive rate under harsh operating conditions. However, the system provided no weed control mechanism. Similarly, (Sujaritha, Annadurai, Satheeshkumar, Kowshik Sharan, & Mahesh, 2017) developed a weed detection robot that used a fuzzy real-time classifier. This system was capable of detecting weeds in sugarcane fields and navigating within the field. The system, however, provided no weed control mechanism.

A gesture-controlled wireless agricultural weeding robot was presented in Gokul, Dhiksith, Sundaresh, & Gopinath, (2019). The robot consisted of an arm that could be remotely controlled using a wearable glove for weed removal. Although made cost-effective by the elimination of optical sensors, the system did not eliminate the need for human intervention and did not incorporate automatic weed identification. In addition, a maize crop and weed species detection system using an unmanned aerial vehicle (UAV) and visible and near-infrared (VNIR) were presented in Pignatti et al., (2019). The system captured images using the UAV and identified weeds using hyperspectral data. However, the system had no weed control mechanism.

Hussmann, Knoll, Czymmek, Meissner, and Holtorf (2019) presented the development of a low-cost delta robot system for weed control applications in organic farming. The system classifies weed via an image acquisition unit and sends coordinates of the weed to the controller. The robot then proceeds to remove the weeds using a weeding tool. Although this system proved effective for weed removal, the setup is not suitable for large outdoor farms. In Sujaritha, Lakshminarasimhan, Fernandez, & Chandran, (2016), a solar autonomous robot was developed for weed control. This robot is powered by solar energy and uproots weeds in a grape field. However, for high accuracy, the weeds need to be isolated, or else the crop could be accidentally uprooted.

Furthermore, in Sabanci and Aydin (2017), a smart robotic weed control system for sugar beet was developed. The system was capable of detecting weeds and spraying herbicide if the need arises. A major limitation of this system is the structure since it cannot be used in the field without significant modifications. Also, in Olaniyi, Daniya, Kolo, Bala, & Olanrewaju, (2020), a weed detection and control system was developed for low land rice precision farming. This system used neural networks and fuzzy logic to detect and control weeds respectively. However, the system still required human intervention as the farmer needed to carry the system around the farm. This increased the stress and fatigue experienced by the farmer.

Based on the aforementioned review, it is evident that there is a need for an improved system to address the research gaps identified. These gaps include:

a. The suitability for use in large farmlands.
b. The elimination of human intervention.
c. The inclusion of control mechanisms for autonomous operation.
d. The incorporation of weed control schemes for weed removal.

The need for an increase in agricultural production in sub-Saharan Africa emerges due to declining oil prices and the need to diversify the region's economy. The vast land and fertile soil available in the region provides the potential for food-producing nations in that area to become giants. This, in turn, will, in the course of time, lead to continental and global food security. Autonomous systems and precision farming play a vital role in boosting farm production.

Therefore, in this paper, a conceptual design of an autonomous robotic system for the identification and chemical control of weeds in a conventional farm setting is proposed. The proposition adopts the use of control theory, computer vision, and artificial intelligence techniques in its navigation and herbicide applications. It is envisaged that upon implementation of this design, the need for manual removal of weeds and associated challenges would be eliminated. In addition, the adoption of this system will result in a decrease in human intervention, stress, and fatigue in crop production. This, in turn, will lead to an increase in revenue and an improvement in the value chain of agribusiness.

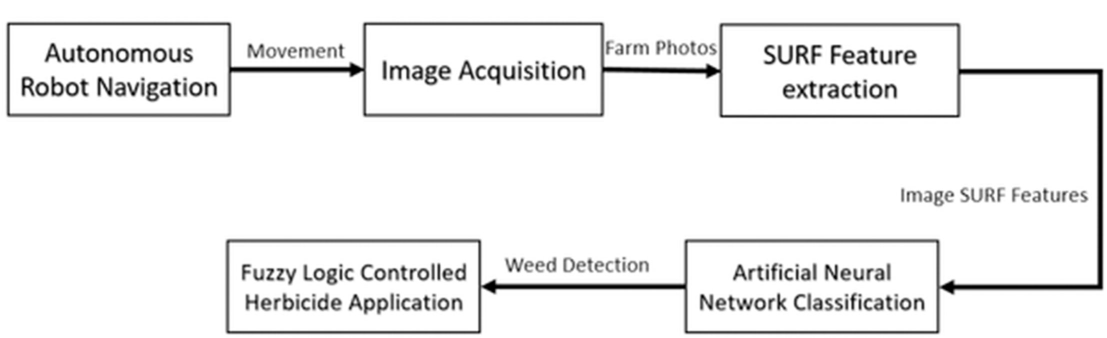
RESEARCH IMPLEMENTATION STRATEGY

This section presents the implementation techniques, specifications, and considerations for the autonomous robot system for chemical weed control. The section covers the theory behind basic concepts used in the development of the system and the description of the various modules that make up the system.

System Overview and Description

The autonomous robot system for chemical weed control consists of various modules that interact to carry out weed detection and control. These subsystems execute robot navigation, weed identification, and herbicide application. The various modules and their interaction are shown in Figure 1.

Figure 1. Dataflow diagram for various system modules



The block diagram for the system architecture is presented in Figure 2. The hub of the system is the Atmega 2560 microcontroller. The choice of this microcontroller is influenced by its powerful abilities, especially in the area of control and automation. Images acquired from the camera are analyzed using the image-processing algorithm and artificial neural network resident on the microcontroller. After the images are processed and weeds are identified, the microcontroller will send control signals to the DC pump for herbicide application. The amount of herbicide to be applied is determined by a Fuzzy control algorithm on the microcontroller. The DC motor and servo motor are used for movement within the farm environment. The direction of the movement is determined by the inputs from ultrasonic sensors. These sensors are used to identify the presence of ridges in the farm and in turn, are used to estimate the location of the robot with respect to the ridges. The circuit diagram of the system is shown in Figure 3.

Figure 2. Block Diagram of System Architecture

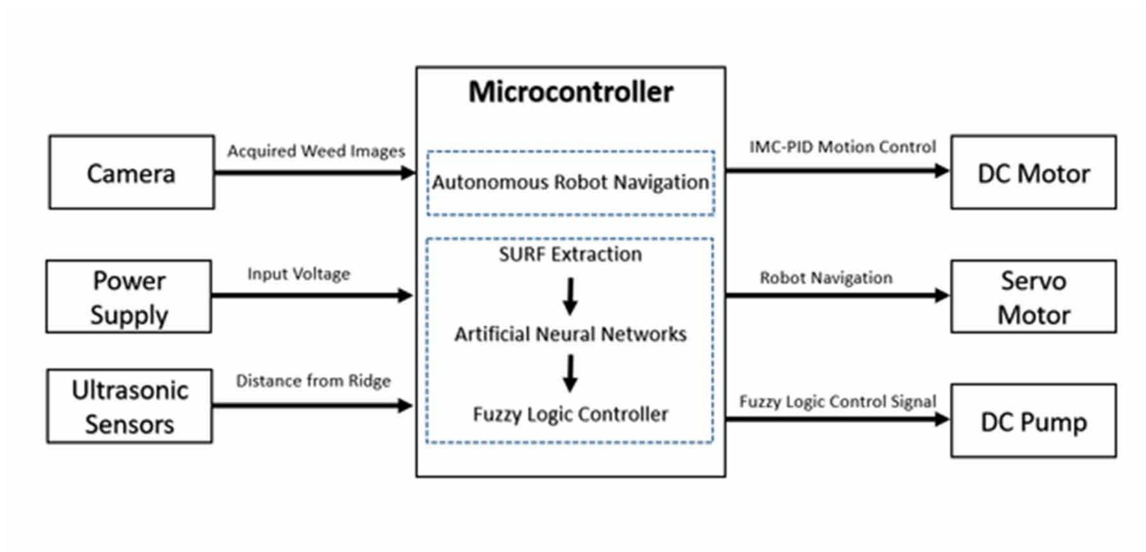
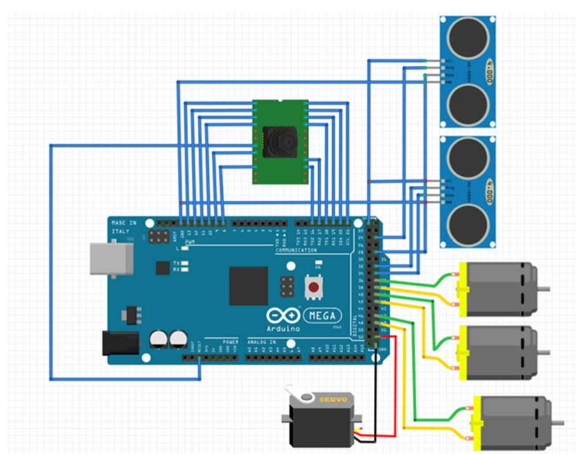


Figure 3. Circuit Diagram of Mobile Robot



Autonomous Robot Navigation within the Farm Environment

The mobile robotic system consists of three wheels (two rear and one front). The rear wheels are driven by a 775 12V DC motor while the front wheel is controlled by a servo motor. Their main function is a movement within the environment. There are two ultrasonic sensors that are used to identify the presence of ridges on the farm. This ensures that the robot moves in between the ridges to ensure proper capturing of the images.

The speed of the system is determined by the DC motor. The system moves at a predefined speed, which is controlled using the relationship shown in equation 1.

$$N = K\frac{V - IaRa}{\varnothing}\,\text{r.p.m} \tag{1}$$

Where:

N = Speed of DC Motor
V = Applied Voltage
Ia = Armature Current
Ra = Armature Resistance
Φ = flux / pole (Theraja & Theraja, 2005).

Equation 1 shows that the speed of the motor is directly proportional to the applied voltage and inversely proportional to the magnetic flux. Hence, the speed can be controlled by varying the applied voltage (voltage control), varying the magnetic flux per pole (flux control) or varying the armature resistance (Rheostatic control).

In the aspect of the robotic navigation, the robot will move between the ridges, and when it reaches the end of the ridge, it will make a left or right turn depending on the previous turn direction. The algorithm for the movement between the ridges is presented as follows:

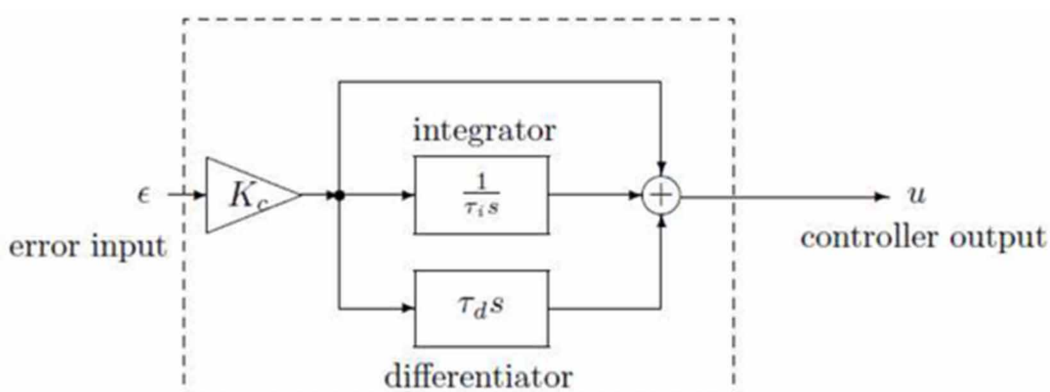
```
function robotNavigation (leftSensorDistance, rightSensorDistance)
define thresholdValue, error as double;
define direction as int;
while(1) {
error = leftSensorDistance – rightSensorDistance;
If (error<=thresholdValue)
direction = 0;
Else
direction = 1;
End If
direction = - direction; }
end function
```

The algorithm shows the technique of movement between ridges on the farm. The robot consists of two ultrasonic sensors, each on the left and right sides of the robot. Evaluating the error (line 5) is carried out to determine if the robot is between ridges or has reached the end of the ridge. This process is achieved by comparing the error with a pre-determined threshold value (line 6). If the error is less than the threshold, the robot continues moving straight between the ridges, a process that is represented by a direction value of 0 (line 7). However, if the robot reaches the end of the ridge, which implies the error is above the threshold, the robot turns either right (direction value of 1) or right (direction value of -1) depending on the previous direction value. This turning motion will make the robot move into the next ridge space.

Motion Control Scheme

To ensure proper robotic movement, system stability, and satisfactory system response, a Proportional-Integral-Derivative (PID) control scheme is used. The PID control scheme is a feedback control technique that is widely used in the control and automation industry. Its high demand is because of its control features and capabilities for a wide range of industrial applications such as DC motors. About 95% of control loops are implemented with a PID controller due to the device's structural simplicity and robust performance in a wide range of applications (Mohindru, Sharma, & Pooja, 2015). In order to achieve a PID scheme with high performance and robustness, the appropriate proportional, integral, and derivative gains of the controller need to be selected. The process of this selection is known as PID tuning. However, the tuning of control parameters to achieve optimum performance is a tedious task. This difficulty is due to the number of parameters involved (three) and finding the appropriate combination has proven to be quite challenging. However, in this case, the PID tuner application provided by MATLAB is used to tune the PID parameters. The application analyses the output from the system model and uses a computational optimization approach to obtain the PID gains. The PID control process is shown in Figure 4.

Figure 4. A PID Control Process (Kambiz & Mpanda, 2012)



Due to the advantages exhibited by the PID controller, in this study, a PID tuning approach is adopted to ensure optimum system response, stability, and accuracy of the robot navigation. In order to implement the PID control scheme, a mathematical representation of the system must be acquired. In the case of this system, the major components are the DC motor, servo motor, and DC pump. These components can be modeled using the transfer function of an electromechanical system given in equation 2.

$$G(s) = \frac{\Omega(s)}{V_a(s)} = \frac{k_t}{(R+LS)(Js+B)+k_t k_b} \tag{2}$$

Where:

Ω = Angular Displacement
V_a = Applied Voltage
R = Armature resistance
L = Armature inductance
J = Rotor inertia
B = Viscous friction co-efficient
K_t = Torque Constant
K_b = Back EMF constant

The values of the parameters are obtained from the DC motor used in the system design obtained in Bala, (2015). These values are as follows:

K_t = 3.475 NM/Amp
K_b = 3.475 V/rad/sec
B = 0.03475 MN/rad sec
J = 0.068 Kg/m^2
L = 0.055H
R_a = 7.56 Ω

Substituting these values in equation 2, we obtain equation 3.

$$G(s) = \frac{3.475}{0.00374S^2 + 0.51599S + 12.33831} \tag{3}$$

After the system has been modeled, the PID transfer function needs to be obtained. The PID transfer function is given in equation 4.

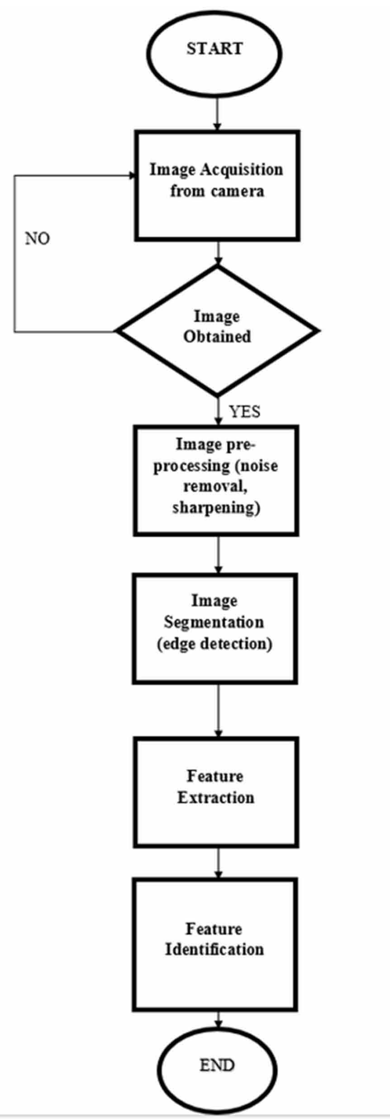
$$G_{PID}(s) = K_p + \frac{K_i}{s} + K_d s \tag{4}$$

Here, K_p, K_i, and K_d respectively represent the proportional, integral, and derivative gains of the controller.

Weed Identification using SURF and ANN

The weed detection module is responsible for identifying weeds on the farm. The module takes an input image from a camera and runs it through an artificial neural network (ANN). The neural network determines if the image input contains weeds or not. If a weed is detected, the herbicide will be sprayed accordingly. The images go through the stages of image processing which are highlighted in Figure 5. After the image is processed and the required features are extracted, the data is passed into the neural network for further processing.

Figure 5. Image Processing Stages



In image processing, feature extraction and feature recognition are essential aspects. These actions are widely used in pattern recognition, object identification, visual navigation, and tracking (Wang, Zou, & Shi, 2018). Popular image feature matching algorithms include the Scale Invariant Feature Transform (SIFT), the Speeded Up Robust Features (SURF), and the Histogram of Oriented Gradients (HOG). The features that are extracted from the images in this study are the Speeded Up Robust Features (SURF). The rationale for the use of SURF lies in its powerful object recognition capabilities and robustness. In addition, the speed of the SURF algorithm makes it suitable for real-time applications (Wang et al., 2018).

SURF is one of the most robust and popular feature extraction techniques in image processing (Rahmani & Narouei, 2020). The algorithm consists of feature point detection, feature descriptor evaluation, and feature point direction identification (Feng, Wang, Yang, & Li, 2019). The detection of the interest points involves the use of a Hessian matrix. The determinant of this matrix reaches the extreme at points of maximum change in the brightness gradient. The Hessian matrix for a two-dimensional function is given in equation 11 (Mukhina & Barkalova, 2018).

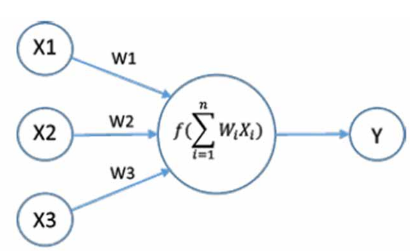
$$H\left(f\left(x,y\right)\right)=\begin{bmatrix}\frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x\partial y}\\ \frac{\partial^2 f}{\partial x\partial y} & \frac{\partial^2 f}{\partial y^2}\end{bmatrix} \tag{11}$$

The SURF algorithm is an improved version of the SIFT algorithm and is characterized by its matching speed and robustness (Wang et al., 2018). After the SURF features are extracted, the data is passed through an Artificial Neural Network for feature identification.

Artificial Neural Networks are powerful mathematical models that attempt to simulate and mimic the operation of biological neural networks. The basic building block of neural networks is the neuron. The output of the neuron sums up all weighted inputs and bias (Krenker, Bester, & Kos, 2011). Neural Networks can perform a wide number of tasks like classification, data processing, decision-making, and robotics.

The neural network is trained using data obtained from images through the process of supervised learning. The neural network is trained using weed images, which are obtained from the Kaggle dataset repository (Kaggle, 2020). The SURF features of these images are extracted and these features form the dataset which is used in the training, testing, and verification of the ANN. 70% of the data is used for training, 15% used for testing and 10% for verification. The neural network is designed based on the structure of a neuron shown in Figure 6.

Figure 6. Artificial Neuron (Oken, 2017)



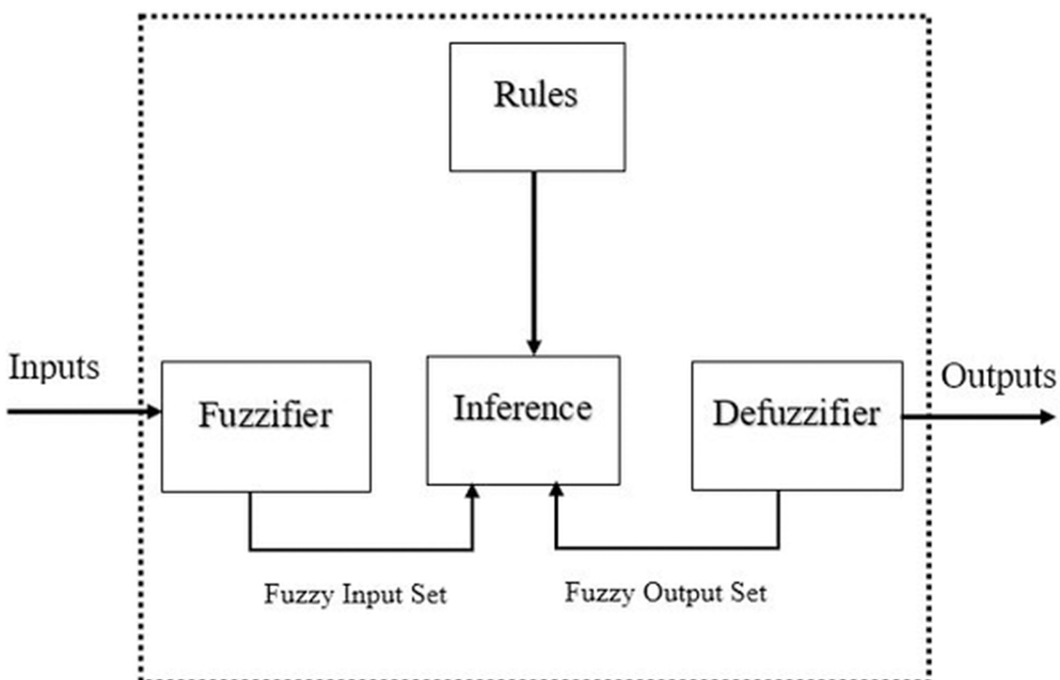
From Figure 6, the variables X1, X2, and X3 represent the inputs, while Y is the output of the neural network. In the case of this study, the inputs to the ANN are the SURF features obtained from the images. The output of the neural network is the classification result obtained from the ANN.

After the data is passed through the neural network, the output determines if a weed is detected or not and, thus, if the herbicide is required or not. The herbicide is applied based on the control signal sent from the fuzzy controller which determines the amount of herbicide to be used.

Herbicide Control Application With Fuzzy Logic

Fuzzy Logic was first introduced by Dr. Lofti Zadeh in 1965 as a technique to model uncertainty and vagueness in natural language (Singh & Mishra, 2015). It is a technique that mimics the human method of reasoning and attempts to make decisions in imprecise situations (Olaniyi, Salami, Adewumi, & Ajibola, 2014). Fuzzy Logic has been an attractive technique in linear and nonlinear control applications, pattern recognition, and even financial systems (Singh & Mishra, 2015). A fuzzy logic system consists of four main parts which are the fuzzifier, rules, inference engine and the defuzzifier (Singhala, Shah, & Patel, 2014). Figure 7 shows a fuzzy logic system.

Figure 7. Fuzzy Logic System



Fuzzification is the process of converting a crisp input into a fuzzy input (Olaniyi et al., 2014). This is usually achieved using membership functions. A membership function is a graphical representation of how a crisp input is mapped to a degree of membership from 0 to 1 (Waris & Ahmad, 2011). There are different types of membership functions used in fuzzy logic, which include triangular, trapezoidal, Gaussian and singleton membership functions (Goni, Gumpy, & Zira, 2018).

After fuzzification is achieved, the fuzzy inference engine evaluates the output based on a set of pre-defined fuzzy rules. Fuzzy rules are conditional statements that evaluate fuzzy outputs from a set of fuzzy inputs (Waris & Ahmad, 2011). Fuzzy rules are usually of the form:

If x is A, then y is B

A and B are linguistic values defined by fuzzy sets. A linguistic value is an input or output value that is not numeric but rather a natural language term (Goni et al., 2018). The first part of the rule is called the antecedent, while the second part is referred to as the consequent (Waris & Ahmad, 2011).

After the inference engine evaluates the rules based on the inputs, a control decision needs to be made. This process is called defuzzification and involves finding a crisp output that summarizes the fuzzy outputs. Some methods of defuzzification include centroid, bisection, weight average, and the largest of the maximum (Olaniyi et al., 2014).

In this study, the Fuzzy Inference System (FIS) was designed using the Fuzzy Logic Toolbox in MATLAB (version R2019a). The Mamdani FIS was used in this study due to its intuitiveness, widespread acceptance, and suitability for human inputs. The inputs to the Fuzzy Controller is the output from the neural network. Based on the developed membership functions, the output of the fuzzy controller will be the amount of herbicide to be sprayed, if required.

RESULTS AND DISCUSSION

This section presents the results from the design of the autonomous robot system for chemical weed control. The section comprises of results from the image processing algorithm, the motion control scheme, and the fuzzy controller for herbicide application.

PID Controller for Movement

From the algorithm of navigation within the farm environment, it can be seen that the robot is required to go left, right or straight depending on the sensor inputs. In order to realize accurate, stable, and effective system performance, a PID control scheme was implemented. The model of the control system is shown in Figure 8.

The PID controller was implemented using Simulink (version r2019). The controller was placed in series with the model of the electromechanical system presented earlier. A step input with an amplitude of 1 was used as the input to the system. The PID controller was tuned using the PID tuner application provided by MATLAB. The application evaluated three appropriate PID gains based on the system response of the transfer function. The system response graph is presented in Figure 9.

Figure 9 has three graphs, namely: the step input, the response of the plant without a control scheme, and the response of the plant with the PID controller. The step input provides a reference signal for all other outputs to follow. This implies that outputs from the plant need to be the same as or close to the reference input.

Figure 8. PID Control Scheme for Robot System

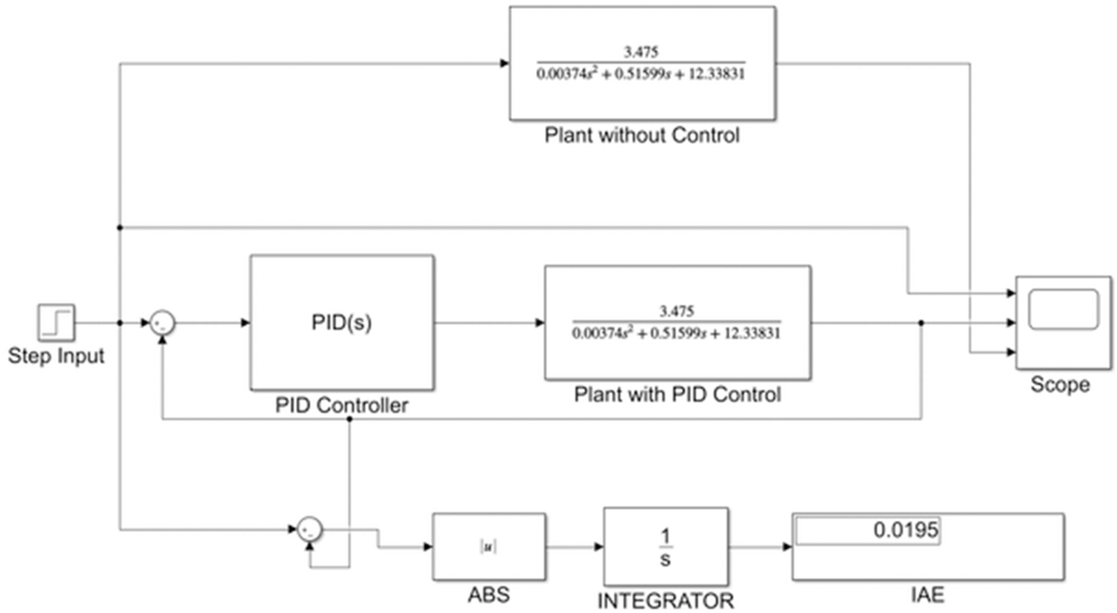
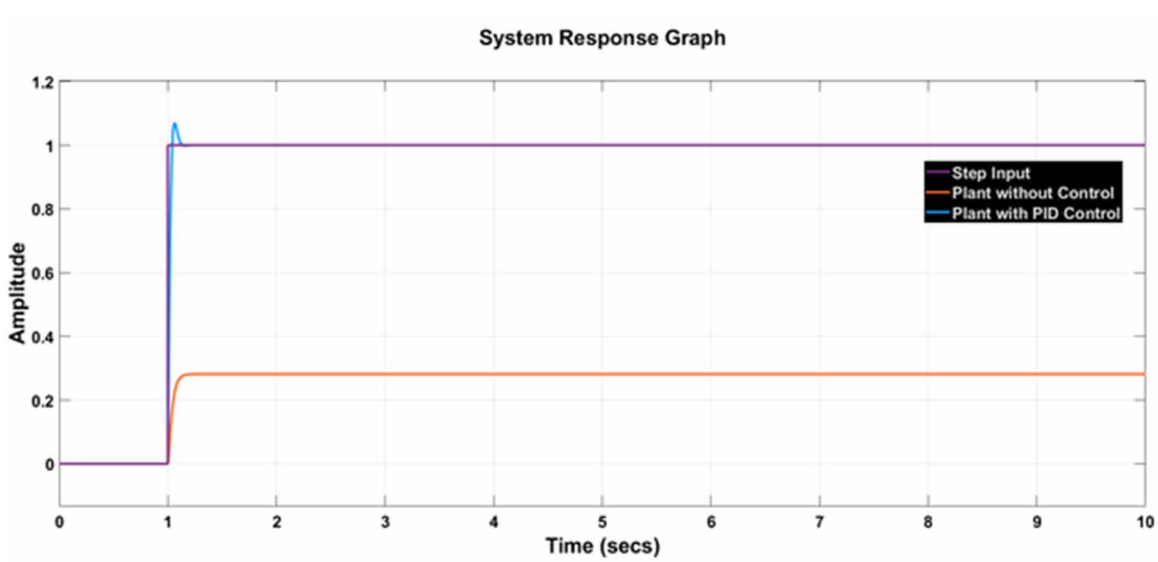


Figure 9. System response graph



On the one hand, the plant without a control scheme has a final value of 0.2 which is much lower than the reference input of 1. This indicates that without a control scheme, the movement of the robot will not be as accurate as required due to a drop in the amplitude. On the other hand, the output of the plant with the PID control scheme closely follows the reference input. This implies that with the PID controller, the robot movement will be accurate and precise.

In terms of the system response performance, Table 1 presents the values of the various metrics used in performance evaluation.

Table 1. System Response Performance

Parameter	Value
Proportional Gain	7.0678
Integral Gain	271.2664
Derivative Gain	0.033725
Rise Time	0.0279 secs
Settling Time	0.102 secs
Overshoot	6.97%
Integrated Absolute Error (IAE)	0.0195

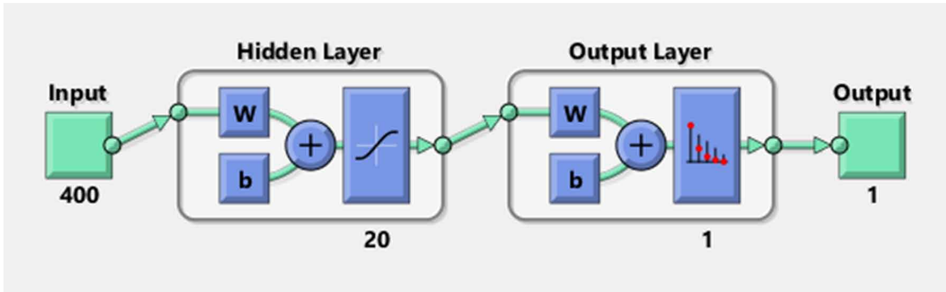
The rise time of the system is 0.034 seconds. This is the time it will take for the system to go from 10% to 90% of the output. This performance shows a fast response by the system. In addition, the system has a settling time of 0.1 seconds. This indicates the time it takes for the system to settle to its final steady-state value. The system has an overshoot of 6.97% which indicates that the output moves past its desired value before settling down at the steady-state value. In terms of the IAE, the system had an error value of 0.0195 for a simulation time of 10 seconds. This value is low and thus, desirable in control performance.

SURF and ANN for Weed Identification

In the area of image processing, 1300 images were obtained from the Kaggle dataset repository. These images consisted of images containing weeds and images without weeds. Each of these images was annotated with either 1 or 0 signifying the presence or absence of weeds, respectively. The class annotations resulted in a dataset of 1300 entities with class values of either 1 or 0. In each of the images, the SURF features were extracted and the strongest 200 SURF features were stored in a database. The resulting database had 1300 entities of 400 SURF coordinates (x and y values) each. This means that each image consisted of 400 parameters. These parameters consist of x and y coordinates of 200 SURF features.

The creation of this dataset was done in order to train, test, and validate the ANN using the process of supervised learning. A neural network was designed with a structure consisting of 400 inputs and 1 output. 20 hidden layers were implemented for the network in order to increase the accuracy of classification. The ANN was designed using the neural network toolbox provided by MATLAB, and the structure of the network is shown in Figure 10.

Figure 10. Structure of ANN



The inputs to the ANN are the SURF features, while the output is the classification result. The neural network was designed using a 70-15-15 rule. This means that 70% of the data was used for training, 15% for testing, and 15% for validation. The network was evaluated using the Receiver Operating Characteristic (ROC) which is a metric for evaluation of classification performance. Figure 11 shows the ROC curve for the ANN.

The ROC curve shows that the curve leans more towards the left, which is desirable in classification. The neural network gave a performance accuracy of 90.7%. This implies that the network will be able to accurately identify weeds in a farm environment.

Fuzzy Logic Controller for Herbicide Application

The Fuzzy Inference System (FIS) was designed in MATLAB (r2019 version). The FIS comprised of one input (weedDetect) and one output (sprayStatus). The input consisted of two triangular membership functions named noWeed and yesWeed, which respectively indicated the absence of weeds and the presence of weeds. Similarly, the output had two membership functions named noSpray and yesSpray, signifying whether or not herbicide is required. Figures 12 and 13 respectively show the membership functions for the input and output.

Figure 11. ROC curve for the ANN

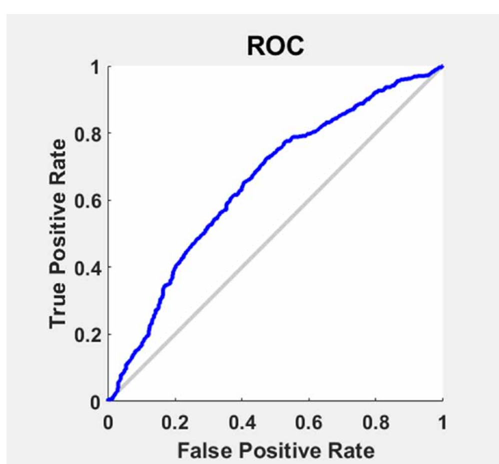


Figure 12. Membership Function for Input

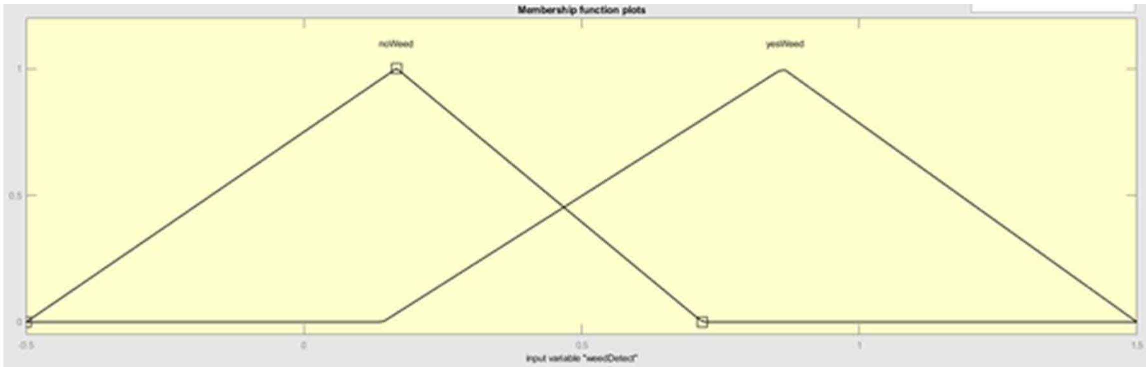
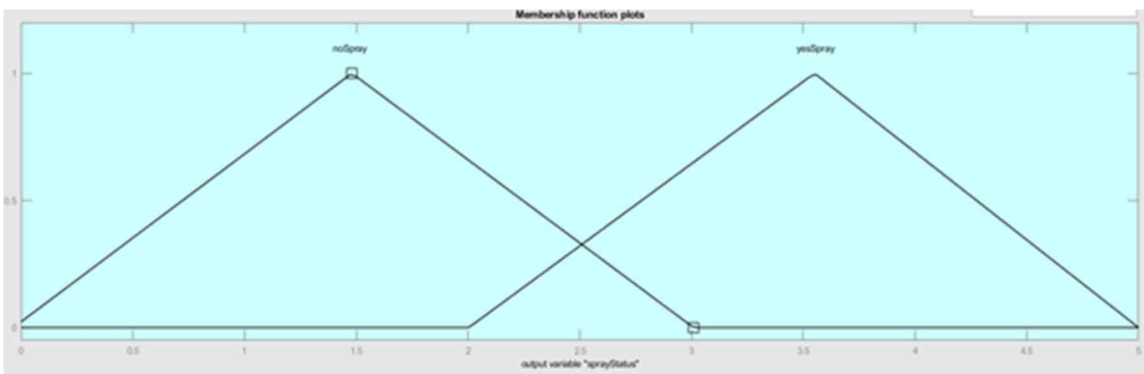


Figure 13. Membership Function for Output



The input to the FIS is the presence or absence of weed. This parameter is obtained from the output of the neural network. The input consists of two membership functions. These functions are noWeed and yesWeed with ranges of -0.5 to 0.72 and 0.14 to 1.5, respectively. The output of the FIS is the application of the herbicide. The output consists of two membership functions which are noSpray and yesSpray with ranges of -0.03 to 3.0 and 2.0 to 5.0 respectively.

The rule base for the FIS consisted of rules developed based on the presence or absence of weeds. If a weed is detected, the herbicide will be applied, and if a weed is not detected, no herbicide is required. The surface view for the rule base is shown in Figure 14, while the rules of the FIS are presented in Table 2.

Figure 14. Surface View for the Rule Base

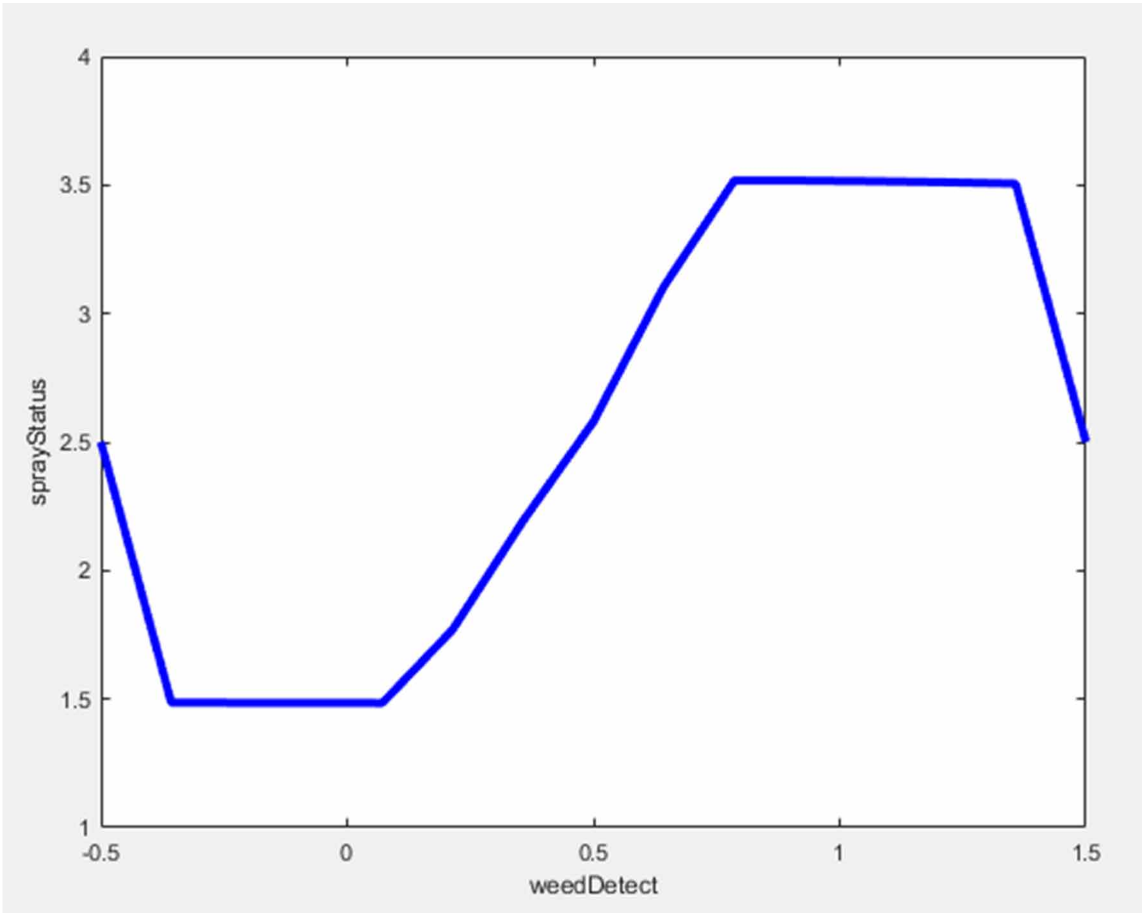


Table 2. Fuzzy Rules

weedDetect	sprayStatus
noWeed	noSpray
yesWeed	yesSpray

CONCLUSION AND FUTURE DIRECTIONS

Conclusion

Agri-business has the ability and opportunity to provide expanded jobs, elimination of hunger, higher income, and boost the production of nutritious food crops. Given the ability of the sector to revolutionize the agricultural commodity production of the Sub-Saharan African region, agribusiness suffers from numerous constraints which include weak policy articulation, insufficient working capital, lack of sufficient technologies and insufficient agricultural infrastructure. These obstacles restrict the industry's sales and earnings. Advances in precision agriculture in terms of the use of smart machines to minimize human involvement have increased agricultural output. The production of robots and their use in agriculture has increased and the possibility of incorporating logical mobile robot solutions based on behavioral approaches has been explored. In this study, the conceptual design of an autonomous robotic system for chemical weed control was presented in a quest to boost crop-based agribusiness productivity.

The autonomous robot system for chemical weed control was designed based on navigation, control, image processing, neural networks, and fuzzy logic techniques. The navigation algorithm presented in the research methodology is used by the robot for movement within the farm environment. To ensure accuracy, stability, and robust performance, a PID controller was implemented. The controller gave a rise time, settling time, overshoot, and IAE of 0.0279 secs, 0.102 secs, 6.97%, and 0.0195 respectively. This indicated a satisfactory system performance. The ANN was developed using SURF features obtained from an image dataset and gave a classification accuracy of 90.7%. The output of the ANN classification is fed into the fuzzy controller, which in turn determines if herbicide application is required. Based on the output of the FIS, the herbicide is applied (or not). The system utilizes visual and ultrasonic sensory inputs to obtain information about the environment. The data obtained from the sensors is analyzed using artificial intelligence algorithms for intelligent farm operations.

The system will enable farmers to cover large areas of arable land with minimal human involvement as regards the minimization of human labor. That implies that farmers could use the system to cover a large area of land instead of hiring a large workforce for manual weeding. Farmers who manage farm operations alone can also introduce this device to simplify their tasks, allowing them the flexibility to concentrate on other operations. It would reduce herbicide application labor costs in crop production substantially. The system will minimize herbicide wastage in the aspect of the application of herbicides. With the autonomous robotic system, the herbicide will only be applied by the device when a weed is detected. This would eliminate the excessive use of herbicide where weeds are not present, thereby reducing the expense of buying herbicides and hiring labor.

This system, upon implementation and adoption, is expected to increase crop yield and profit for agroprenuers with minimal human intervention. In addition, crop production of staple foods in sub-Saharan Africa will be positively influenced due to the potential of the system to encourage crop production on a large scale. This will also improve national and regional food crop production and generate more revenue in the value chain of a crop commodity.

Future Research Focus

The following areas are suggested for future research works.

1. Prototype Development and Hardware Implementation: This will involve the implementation of the algorithms on microcontroller firmware and evaluating the performance of the system in the field.
2. An assessment of robot navigation, weed detection, and herbicide application accuracy on its metric performance in farmers' fields.
3. Field Experimental Assessment: Conduct the comparative efficiency of the Autonomous Robot System with the conventional methods of chemical weed control in a named crop commodity in farmers' fields.

RECOMMENDATIONS

The following recommendations are made for researchers and stakeholders in the agricultural sector:

a. Provision of funding for research and development in smart farm systems to boost agricultural productivity.
b. Sensitization and workshops for farmers on the importance of precision agriculture to agricultural development.
c. Promotion of intelligent and automated farm systems, especially in rural areas, to improve the adoption of state-of-the-art technologies by farmers and to boost crop production of staple foods in sub-Saharan Africa.

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KEY TERMS AND DEFINITIONS

Artificial Neural Networks: Artificial neural networks are mathematical models that attempt to simulate and mimic the operation of the human brain.

Control System: A control system is a system that comprise of processes and subsystems which are integrated for the main purpose of achieving a desired output or performance when given a specified input.

Fuzzy Logic: Fuzzy logic is a method that deals with inaccuracy and indecision. Fuzzy logic imitates the way the human brain works to solve problems, thereby aiding a system to make the right decision in imprecise situations.

Herbicide: This is any chemical or agent used to inhibit plant growth.

Image Processing: This is a technique or process that makes a software identify, analyze, and understand the content of video and images.

Robot: A robot is an electromechanical system capable of performing a pre-programmed mission. Such tasks can be difficult for humans to perform, or repeated tasks requiring accuracy.

Weed: Weed is any plant that grows in an unwanted place.

Appendix 1 (SURF Algorithm)

```
clc;
clear;
myDirectory = dir('data');
surfData = [];
surfClasses = [];
for i = 3:2602
if(rem(i, 2) == 1)
img = imread(strcat('data\', myDirectory(i).name));
gray_img = rgb2gray(img);
new_img = imresize(gray_img, [200 200]);
surfpoints = detectSURFFeatures(gray_img);
strongpoints = surfpoints.selectStrongest(200);
strongpointsLocation = strongpoints.Location;
strongpointsMatrix(1:200) = [strongpointsLocation(:, 1)];
strongpointsMatrix(201:400) = [strongpointsLocation(:, 2)];
surfData = [surfData; strongpointsMatrix];
else
if(rem(i, 2) == 0)
textFileName = strcat('data\', myDirectory(i).name);
textValues = importdata(textFileName);
surfClasses = [surfClasses;textValues(1)];
end
end
end
save('dataset.mat', 'surfData');
save('dataClasses.mat', 'surfClasses');
```

Appendix 2 (ANN Design)

```
% Solve a Pattern Recognition Problem with a Neural Network
% Script generated by Neural Pattern Recognition app
% Created 14-May-2020 15:05:02
%
% This script assumes these variables are defined:
%
% surfData - input data.
% surfClasses - target data.
```

```
x = surfData';
t = surfClasses';
% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. Suitable in low memory situations.
trainFcn = 'trainscg'; % Scaled conjugate gradient backpropagation.
% Create a Pattern Recognition Network
hiddenLayerSize = 10;
net = patternnet(hiddenLayerSize, trainFcn);
% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.input.processFcns = {'removeconstantrows','mapminmax'};
% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivision
net.divideFcn = 'dividerand'; % Divide data randomly
net.divideMode = 'sample'; % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'crossentropy'; % Cross-Entropy
% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
'plotconfusion', 'plotroc'};
% Train the Network
[net,tr] = train(net,x,t);
% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)
tind = vec2ind(t);
yind = vec2ind(y);
percentErrors = sum(tind ~= yind)/numel(tind);
% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
```

```
testPerformance = perform(net,testTargets,y)
% View the Network
view(net)
% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, ploterrhist(e)
%figure, plotconfusion(t,y)
%figure, plotroc(t,y)
% Deployment
% Change the (false) values to (true) to enable the following code blocks.
% See the help for each generation function for more information.
if (false)
% Generate MATLAB function for neural network for application
% deployment in MATLAB scripts or with MATLAB Compiler and Builder
% tools, or simply to examine the calculations your trained neural
% network performs.
genFunction(net,'myNeuralNetworkFunction');
y = myNeuralNetworkFunction(x);
end
if (false)
% Generate a matrix-only MATLAB function for neural network code
% generation with MATLAB Coder tools.
genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
y = myNeuralNetworkFunction(x);
end
if (false)
% Generate a Simulink diagram for simulation or deployment with.
% Simulink Coder tools.
gensim(net);
end
```