Developing a fuzzy logic controlled agricultural vehicle

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Abstract

This paper describes the design of a fuzzy controlled autonomous robot for use in an outdoor agricultural environment for crop following. The robot has to navigate under different ground and weather conditions. This results in complex problems of identification, monitoring and control. In this paper, a fuzzy controller is identified which when used in conjunction with a novel outdoor sensor design deals with both crop tracking and cutting. The controller was tested on an indoor mobile robot using two ultrasound sensors. The controller showed a good response in spite of the irregularity of the medium as well as the imprecision in the ultrasound sensors. The same controller was then transferred to both an electrical and diesel powered robots which operate in an out-door farm environment. These outdoor robots have used our novel sensor (mechanical wands) as well as outdoor ultra sound sensors. The robot had been tested in outdoor environments on fences and real crop edges. The robot displayed a good response following irregular crop edges full of gaps under different weather and ground conditions within a tolerance of roughly 50 mm.

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1. Introduction

The problem of a decreasing agricultural workforce is universal. Therefore, there is a need for automated farm machinery, ultimately including unmanned agricultural vehicles. Many machinery operations in agriculture are essentially repetitive and work with crops planted in rows or other geometric patterns. These operations involve making a vehicle drive in straight lines, turn at row ends and activate machinery at the start and finish of each run. Examples of this are seen in spraying, ploughing and foraging.

In agriculture, the inconsistency of the terrain, the irregularity of the product and the open nature of the working environment result in complex problems of identification, control and dealing with sensing errors. These problems include dealing with the consequences of the robotic tractor being deeply embedded into a dynamic and partly non-deterministic physical world (*e.g.* wheelslip, imprecise sensing and other effects of varying weather and ground conditions on sensors and actuators). Fuzzy logic excels in dealing with such imprecise sensors and varying conditions which characterises these applications.

Artificial intelligence (AI) techniques including expert systems and machine vision have been successfully applied in agriculture. Recently, artificial neural network and fuzzy theory have been utilised for intelligent automation of farm machinery and facilities along with improvement of various sensors. Ziteraya and Yamahaso (1987) showed the pattern recognition of farm products by linguistic description with fuzzy theory was possible. Zhang *et al.* (1990) developed a fuzzy control system that could control maize drying. Ollis and Stentz (1996) has used machine vision to follow and cut an edge of a hay crop but he did not address the problem of turning around at the end of bouts or the detection of the end of a crop row. Cho and Ki (1996) has used a simulation of a fuzzy unmanned combine harvester operation but he used only on-off touch sensors for his fuzzy systems and hence lost the advantage of fuzzy systems in dealing with continuous data which had led him not to have smooth response and gave him problems when turning around corners. It must also be noted that all of his work was in simulation which is different from the real world farm environment. Yamasita (1990) tested the practical use of fuzzy control in an unmanned vehicle for use in greenhouses. Mandow *et al.* (1996) had developed the greenhouse robot Aurora, but the application and environment variation in greenhouses are more restricted and controlled than those in the field. Little work has been done in implementing a real robot vehicle using fuzzy logic which can operate in the open field.

The aim of this paper is to develop a fuzzy vehicle controller for real farm crop following. An emulation of 'crop-

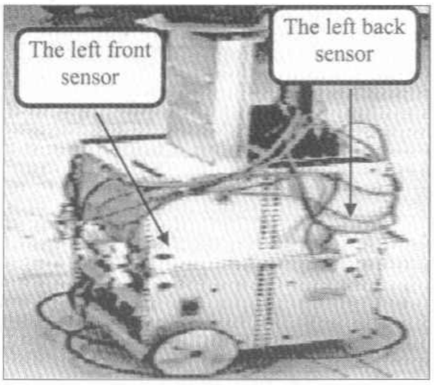

Fig. 1 The indoor robot and its sensor configuration

following' (which is also an example of fence following) is presented and its response and control surfaces are analysed. Then the same control architecture was moved to our outdoor robots. These robots are equipped with special outdoor sensors (a mechanical wand and an outdoor ultra sound sensor) which are designed to deal with the crop characteristics. The fuzzy controller has succeeded in following various outdoor crop and fence edges ranging from metal structures, lines of trees, to crops of hay (including irregular edges which include small gaps) within a tolerance of 50 mm. It has shown it ability to turn different kinds of corners smoothly and worked in a variety of weather and ground conditions.

2. Problem definition

In this section, we introduce the architecture of the robot and describe our novel sensor design which is suitable for sensing crop boundaries. The robot is designed to mow a crop by following its edge while maintaining a safe distance from the uncut edge, in this case 450 mm. While the development work has been based on mowing, the team have taken into account the requirements of other fieldwork operations.

Initially, we have tested our design with an indoor mobile robot, introducing to it all the hard conditions that it might encounter in a real field. Although there are clearly big differences between the indoor environment and that in the field, we have done what we could to make the experiments more realistic, such as using noisy and imprecise sensors, irregular geometrical shapes and fences constructed from baled hay. However, it is self evident that ultimate test of a farm robot is in the field and we thus included as a subsequent stage an assessment based on the use of our outdoor electric and diesel -vehicles. We feel that this approach is better than a computer simulation which suffers from well known modelling difficulties (especially when trying to model the physical environment comprising varying ground and weather conditions and objects such as trees telegraph poles).

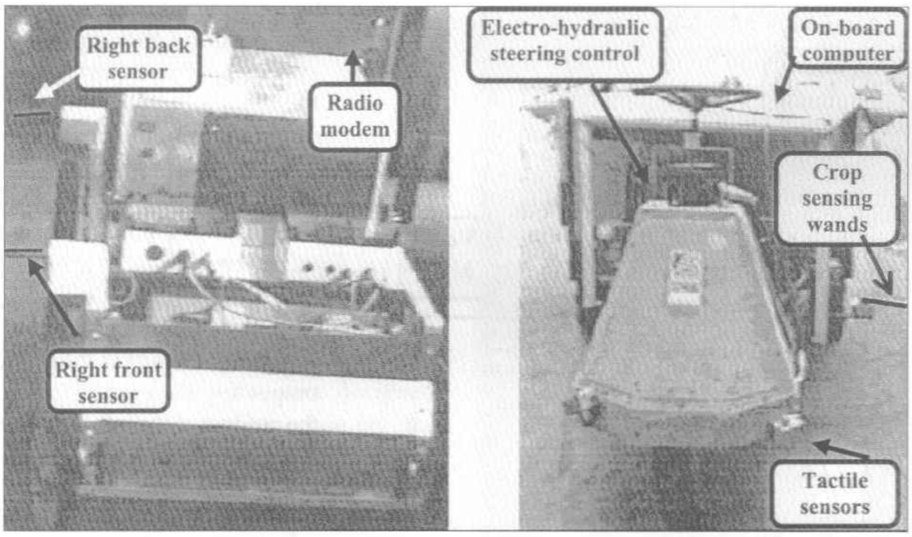

Fig. 2 (a) The outdoor electrical robot; and (b) the outdoor diesel robot

2.1. The robot description

The diesel field robot is constructed on the chassis of a three wheel farm truck. The engine is a New Holland three cylinder diesel engine coupled to a hydrostatic transmission to the differential. Hydrostatic transmission was chosen as providing a simple clutchless transmission. Steering power is provided by an auxiliary pump to a non balanced double acting ram. This was chosen as providing a more complex control problem than a balanced ram would have done. The electric outdoor robot is about the size of a wheelchair and indeed utilises many wheelchair parts. Both robots have mechanical wands (potentiometer arms connected to analogue to digital converter to sense the edge of a crop), ultra-sound sensor, global positioning system (GPS), and a camera. The camera forms part of a system developed by our group (Schallter, 1996) to locate hay bales. The electric robot have two separate motors for traction and steering.

The indoor robot shown in *Fig. 1* has a ring of seven ultrasonic proximity detectors, an 8-axis vectored bump switch and an infrared (IR) scanner sensor to aid navigation. It also has two independent stepper motors for driving the front wheels, with steering by driving at different

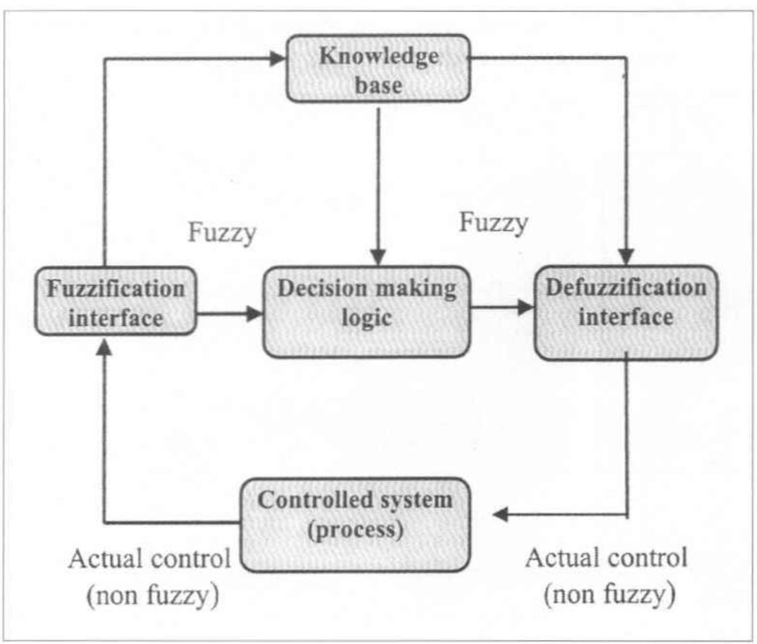

Fig. 3 The basic configuration of a fuzzy logic controller

motors speeds. We try to give all our robots a similar architecture (to simplify development work) so its hardware is also based on embedded Motorola processors (68040) running VxWorks RTOS.

Other papers reported problems using certain types of sensor in outdoor environments. One reported solution uses simple touch sensors (Cho &Ki, 1996) which have ON-OFF states only which is not efficient for fuzzy control. However, we have designed a mechanical wing which is simply an 80 cm. elastic rod connected to a variable potentiometer providing a varying voltage which can then be converted to digital value through an analogue to digital converter. In this way, we can have a cheap sensor which gives a continuous signal monitoring distance from the crop edge (and other obstacles). The sensor configuration for crop harvesting implemented on the electrical vehicle is shown in *Fig. 2a* and the diesel robot is shown in *Fig. 2b*, the outdoor robots are also equipped with ultrasound sensors which are characterised by high noise immunity level.

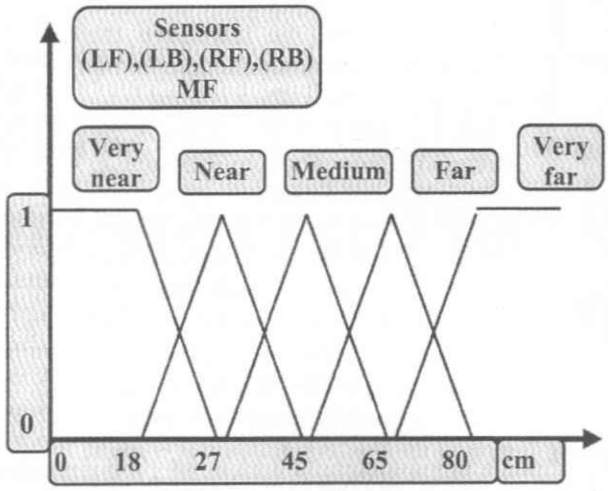

Fig. 4 The membership functions (MF) of the input sensors; LF, left front; LB, left back; RF, right front; RB, right back

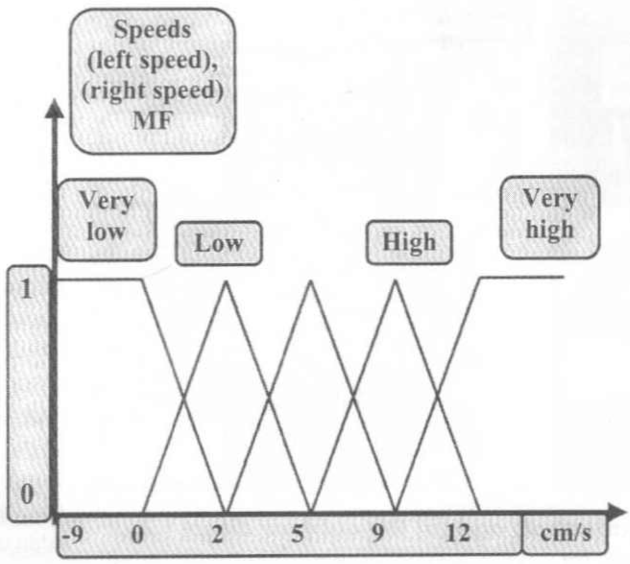

Fig. 5 The membership functions (MF) of the indoor robot output speeds

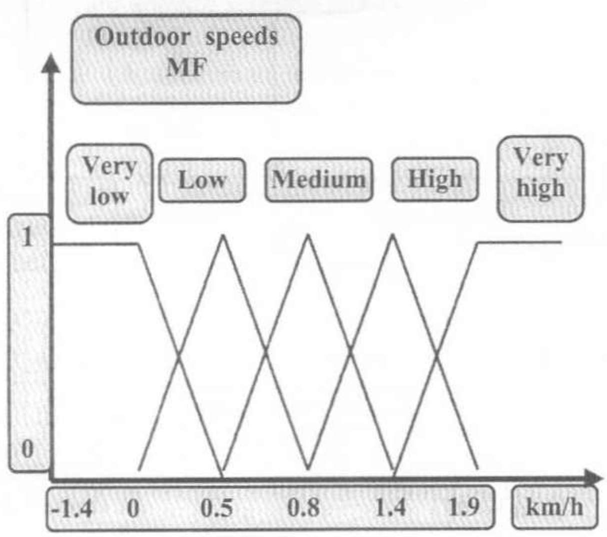

Fig. 6 The output membership functions (MF) of the outdoor robot speed

3. The fuzzy logic controller design

Lotfi A. Zadeh introduced the subject of fuzzy sets in 1965 (Zadeh, 1965). In that work, Zadeh suggested that one of the reasons humans are better at control than conventional controllers is that they are able to make effective decisions on the basis of imprecise linguistic information. He proposed fuzzy logic as a way of improving the performance of electromechanical controllers by using it to model the way in which humans reason with this type of control information. *Figure 3* shows the basic configuration of a fuzzy logic controller (FLC), which consists of four principal components which are the fuzzification interface, knowledge base (comprising knowledge of the application domain and the attendant control goals), decision making logic (which is the kernel of an FLC), and defuzzification interface.

In the following analysis, we use a singleton fuzzifier, triangular membership functions, product inference, max-product composition, height defuzzification. These techniques are selected due to their computational simplicity. The equation that maps the system input to output is given by:

$$\frac{\sum_{p=1}^{M} y_p \prod_{i=1}^{G} \alpha_{Aip}}{\sum_{p=1}^{M} \prod_{i=1}^{G} \alpha_{Aip}}$$

where: M is the total number of rules; y is the crisp output for each rule;$\alpha\alpha_{Aip}$ is the product of the membership functions of each rule inputs; and G is the total number of inputs. More information about fuzzy logic can be found in Lee (1990).

The membership functions (MF) of the inputs denoted by left front (LF) sensor and the left back (LB) sensor [right front (RF) sensor and right back (RB) sensor in the case of the outdoor robots] are shown in *Fig. 4*. The output membership functions shown in *Fig. 5* are the left and right speeds for the indoor mobile robot, the robot steering being performed by moving at different wheel speeds. The outdoor memberships are the same for the inputs sensors (in spite of using different sensors from the indoor robots). As the outdoor robots have a steering motor, the output membership functions consist of speed in *Fig. 6* and the steering parameters in *Fig. 7*.

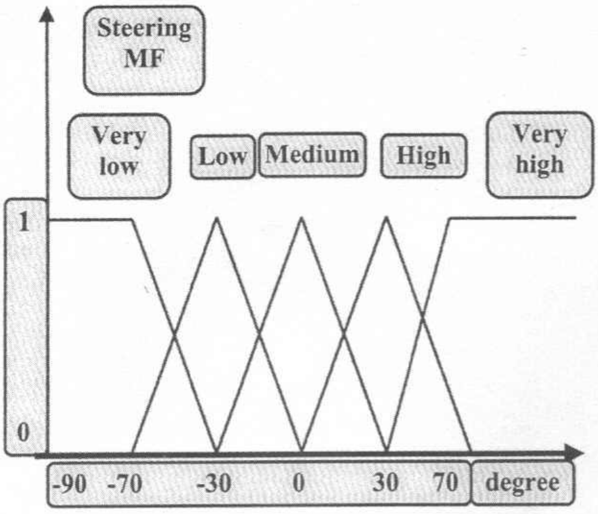

Fig. 7 The output membership functions (MF) of the outdoor robot steering

The rule base of the indoor controller is the same for the outdoor robots except for speed and steering aspects. Also the indoor robot was left edge following while in the outdoor robots it will be right edge following (a peculiarity of the fact the vehicles were built by different people). These rule bases and the membership functions were designed using human experience but we are developing methods to learn them automatically using genetic algorithms.

Figures 8 and 9 represent the control surfaces of the indoor and the outdoor robots. *Figure 8* represents the indoor robot control surface in which the LF and the LB were plotted against their outputs which are the left speed (left figure) and the right speed (right figure). *Figure 9* represents the control surface of the outdoor robots in which RF and RB were plotted against their outputs which are the robot speed (left figure) and the robot steering (right figure).

4. Experimental results

The performance of the architecture has been assessed in two main ways. Firstly, we physically emulated (rather than simulated) the crop following process. In this emulation, we have conducted practical experiments with the indoor robots to track the robots paths and reactions to the irregular geometrical shapes forming fences that fake the crop edge. These fences included one formed with real bales of hay which are real challenge to the robot because of their irregularity and low sensitivity of sonar sensors toward them. In the next phase, we have tried the same architecture in the outdoor environments to track fences and real crop edges in real farms. Each experiment was repeated five times and each time the path was recorded to test the system repeatability and stability against different weather and ground conditions (such as rain, wind, holes in the ground, going up and down hill, *etc.*). *Figure 10a* shows the robot emulating the crop cutting operation. Here it continues going inwards to complete the harvesting operations. The cutting action was simulated by reducing the size of the fence. Note that the response is smooth especially when the robot turns. This is due to the smooth transition between rules and the smooth interpolation between different actions which are characteristics of fuzzy logic. The same experiment was repeated but with real bales of hay and gave a very smooth and a repeatable

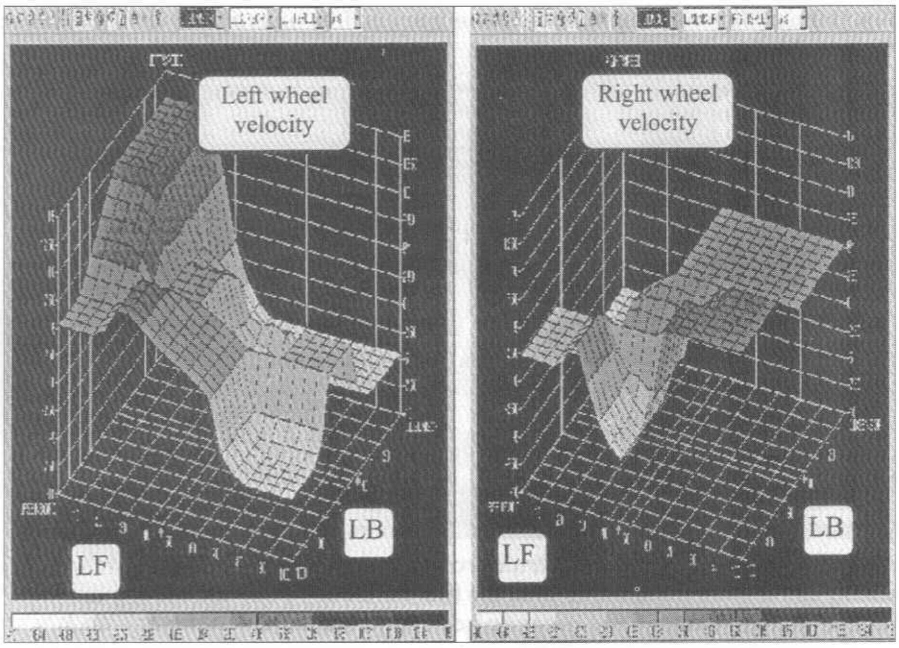

Fig. 8 The control surface of the indoor robots; LF, left front sensor; LB, left back sensor

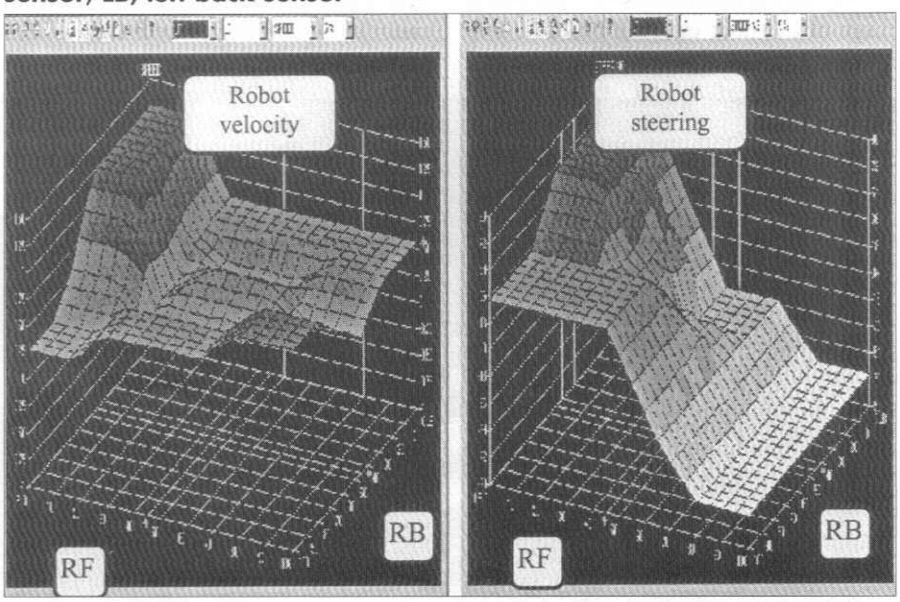

Fig. 9 The control surface of the outdoor robots; RF, right front sensor; RB, right back sensor

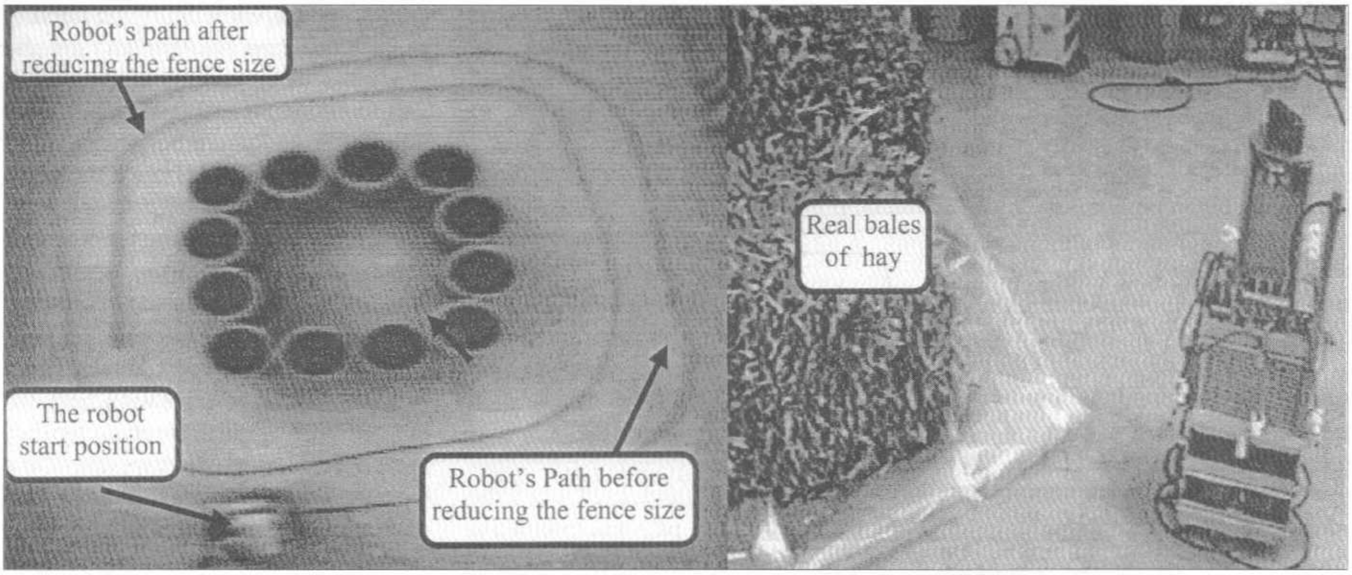

Fig. 10 (a) The robot emulating the harvesting operation; and (b) the robot following fences formed by bales of hay

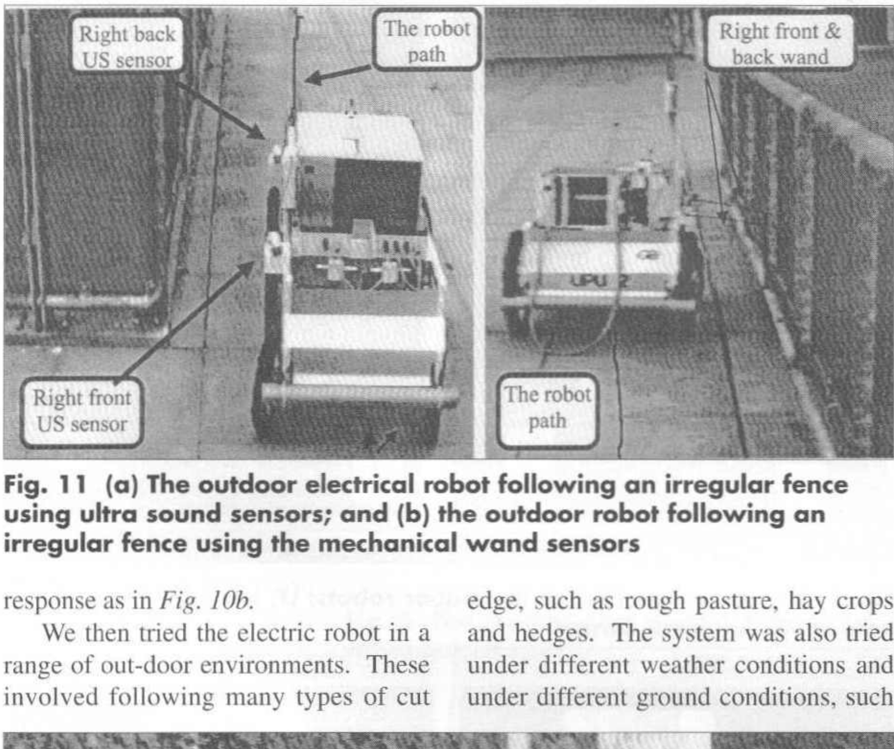

Fig. 11 (a) The outdoor electrical robot following an irregular fence using ultra sound sensors; and (b) the outdoor robot following an irregular fence using the mechanical wand sensors

response as in *Fig. 10b.*

We then tried the electric robot in a range of out-door environments. These involved following many types of cut edge, such as rough pasture, hay crops and hedges. The system was also tried under different weather conditions and under different ground conditions, such as mown turf, hay stubble and ground that was rutted. It was also tested on flat land as well as on slopes, both up and down and across the slope.

The same control architecture was used in all robots only varying the output (MF) of the robots and slightly varying the rule base to cater for the differing steering and speed characteristics of the robots. We experimented with mechanical wands and ultra sound sensors. In spite of the varying weather conditions, the systems displayed a very good response showing the fuzzy controller can deal with imprecision and noise.

Figures 11a and11b show the robot path of the electrical outdoor robot following an outdoors fence. In *Fig. 11a,* the robot succeeded in following an irregular rectangular metallic fence under different weather conditions (*i.e.* wind

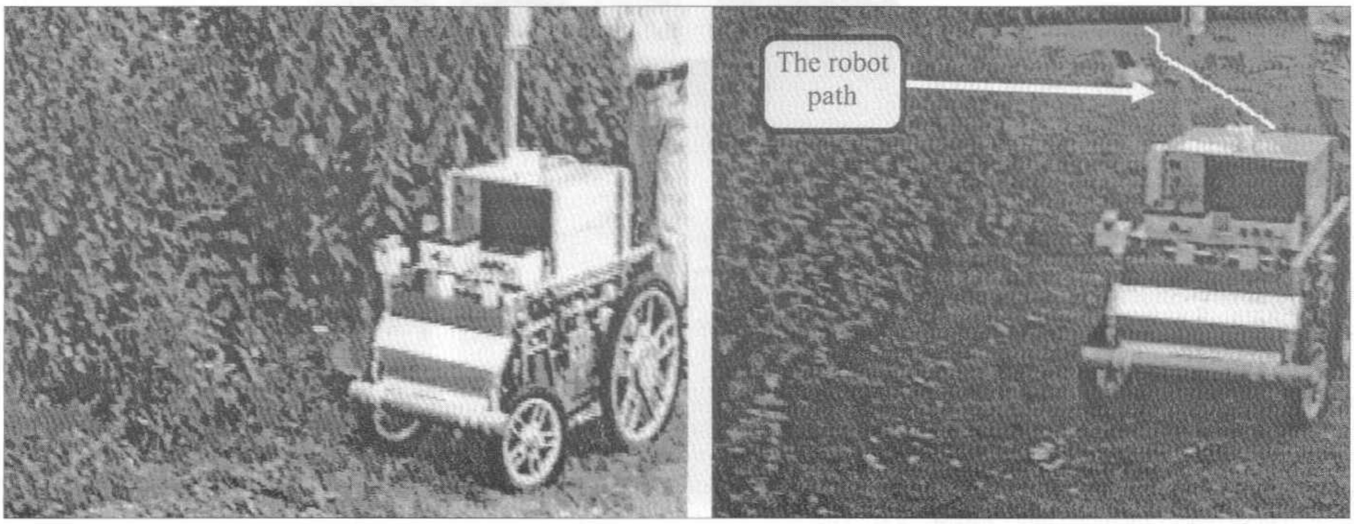

Fig. 12 (a) The electrical robot following out door irregular tree hedges; and (b) the robot path

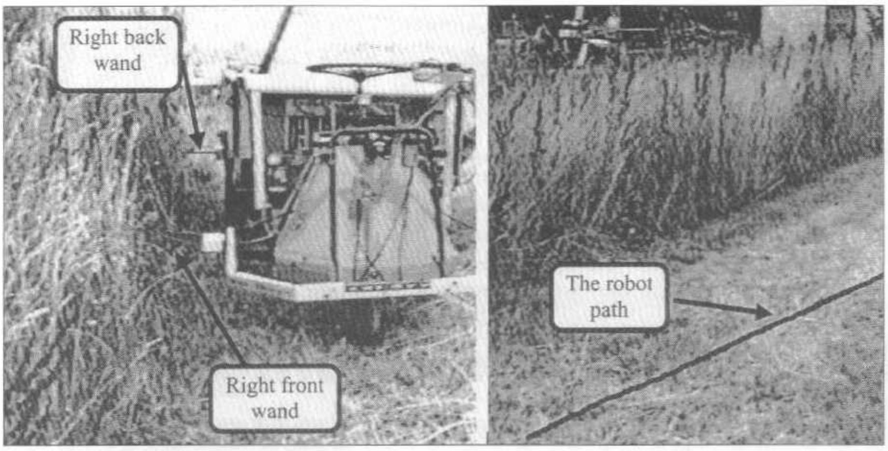

Fig. 13 (a) The diesel robot following real irregular hay crop edge using the mechanical wands; and (b) the robot path

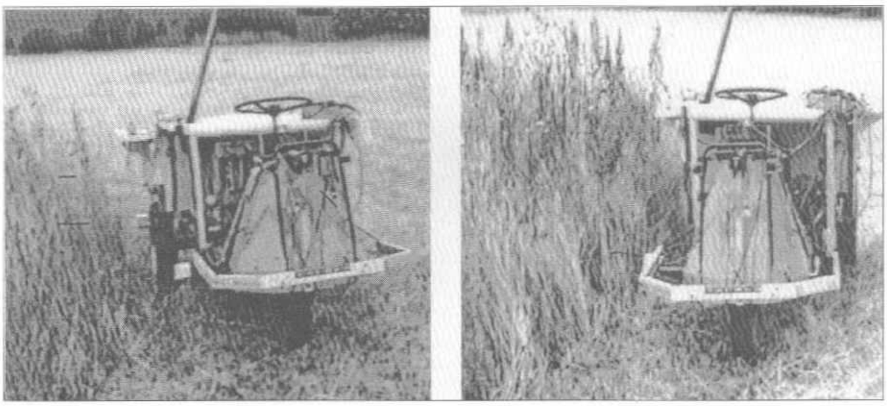

Fig. 14 (a) The robot starts turning around an irregular hay crop corner; and (b) the robot after turning smoothly around the corner

and rain) using only two ultra sound (US) sensors. The robot gave repeatable and smooth path following on the whole fence, as well as turning around corners. *Figure 11b* shows that the robot succeeded in following the same fence using the mechanical wands, the robot again following the fence with high repeatability and stability and responding rapidly but smoothly to any changes in the fence line.

Figure 12a shows the electrical robot in the field following a crop edge which is characterised by high irregularity (gaps in the edge, plants falling from the edge). The robot was also required to navigate uphill and downhill in a ground full of ruts. It used two ultra sound sensors to sense the crop edge. Again the robot gave a smooth response and followed the crop keeping a safe distance from the crop edge and responding rapidly but smoothly to any changes in the edge *Fig. 12b*. Although we currently have no quantitative means for evaluating the precision of the crop following, we estimate that the crop edge was tracked successfully within a tolerance of 50 mm.

Figure 13a shows the diesel robot with the mechanical wand sensors in a hay field that has a very discontinuous edge and ill defined corners. The robot gave stable, repeatable and robust response as shown in *Fig. 13b*, and tracked the edge of the crop successfully within a tolerance of 50 mm. The robot also turned smoothly around the ill-defined hay crop corners, as shown in *Fig. 14a*. *Figure 14b* shows the robot after turning smoothly around this corner.

5. Conclusions

In this paper, we have developed a fuzzy controller for a robot aimed at automating the crop following processes. We have developed a novel sensor design (outdoor mechanical wands) to be used in real farms under different conditions. We tested the fuzzy control architecture on an indoor mobile robot with only two ultrasound sensors. It had succeeded in maintaining itself at a constant distance from the crop in spite of boundary irregularities and the imprecision in the ultrasound sensors. After testing the architecture successfully indoors, the control architecture was moved to the outdoor robots. In the field environment, the robots displayed a smooth and fast response and were able to track various edges under different weather and ground conditions.

The outdoor robots tracked irregular crop edges successfully within a tolerance of 50 mm. The robot also turned around real crop corners smoothly and gave a highly repeatable and stable response. To the authors' knowledge, the work described in this paper is the only system which has successfully guided a diesel tractor in the outdoor environment, following real crop edges (including irregular edges which include gaps) and turning around corners with a high degree of repeatability and following the crop edge with a tolerance of 50 mm. The system is totally autonomous with no pre-specified plans and reacts in real time to the changing field conditions.

We are currently investigating the performance of other farm tasks (such as the collection of bales of hay or fruit boxes). In these, we are going to use a fuzzy hierarchical controller to combine several behaviours for safe navigation toward our goals. In this work, we will integrate a vision system for bales of hay detection and will try to integrate it with the fuzzy system for reactive navigation. Also, we are currently investigating the use of GA based methods in respect to adding a learning capability to the controller so that it can adapt itself to the changing conditions of a field.

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Lantra report points to increasing requirement for higher skills levels

The latest research into labour market trends by Lantra (the National Training Organisation for land-based industries) shows that there is an increasing need for higher levels of skills in most land-based industries. Traditional unskilled and semi-skilled jobs are in decline and skills levels have to rise to meet the challenges of new working practices, rapid developments in technology and increasing competition.

The report, launched at the Farmers Club, London on 19 February states that 10 years ago many land-based employees needed skills equivalent to, or just above, level 2 in a National or Scottish Vocational Qualification (N/SVQ). This has increased to level 3 or higher. Other key findings from the report include:

- workforce turnover is increasing and averages 14%
- 43% of workers have industry-relevant qualifications at N/SVQ level 2 or above
- 26% of the workforce is qualified to level 3 or above
- an average of only 1.3 days per person was spent on training last year
- less than 25% of land-based businesses arrange formal training
- only 10% of land-based businesses have a formal training plan

The labour market information report presents the results of a two-year project through which Lantra has collected information from over 7,500 businesses operating in all aspects of the landbased sector across Great Britain. As well as providing the basis for the report, this data is also held in an economic forecasting database which can be used to help predict future demand for numbers of workers and their skill levels.

In the report's foreword, minister for lifelong learning Malcolm Wicks said: 'The data gathered in this report will serve as a solid foundation on which to develop the necessary foresight to future skills needs of the land-based industries. Naturally, this is a continuous process and this report only represents the first step in a much larger journey. Lantra must now gather support from employers, education and training providers, trade associations and others to develop a full Skills Foresight report and to put in place the measures necessary to address future skills needs.'

Lantra's chairman Andy Stewart said: 'The report highlights the difficult times now facing many parts of the land-based sector. These new challenges will have to be met by existing or future recruits and are likely to demand new skills and competences. If businesses are to compete effectively, employers must understand which skills are needed and take action to ensure that they exist in the workforce.

The report was used as the basis for a conference on 29 February for employers, trade association staff and education and training providers. 'This provided an opportunity for the sector to discuss the significance of Lantra's findings and shape a full skills-foresight report which we aim to publish in May' said Mr Stewart.

Contact: **Copies of the report are available from Lantra Connect on 0345 078007.**

Gentle new potato planter boosts planting accuracy

Kverneland has launched a brand new two row potato planter in time for this Spring's planting season. Designated the UN 3000T, the new planter boasts two major new benefits aimed at improving planting efficiency.

The first is an Hydraulically tipping 1.5 tonne capacity hopper, which has been found to be extremely gentle when handling chitted seed. The hopper feature is ideal for larger potato growers who require increased efficiency from a compact and manoeuvrable planter, especially when working long runs.

The second new feature is electronic vibrating agitation. The cupped belt vibrates from top to bottom, ensuring that only one potato per cup is delivered down. The degree of agitation is variable to suit different working conditions and tuber sizes, and the system has proven itself far more reliable and accurate than standard 'one bump' manual systems. The vibrating agitation system can also be fitted to the standard Kverneland UN 3000 planter.

The UN 3000T retains many of the well proven and popular features of the existing UN 3000 range, including a large planting unit with 74 mm cups as standard to handle large sized tubers, a top drive shaft for cup belts, and spacing that is adjustable from the side of the planter. A ridging hood is also available in lieu of the standard ploughs.

Retail price for the new UN 3000T planter is from £7,990 complete with the new agitation system.

Contact: **Les Davidson, Potato Product Manager, Kverneland (UK)**