APPLICATION OF NEURO-FUZZY CONTROLLER TO AUTONOMOUS AGRICULTURAL VEHICLE OPERATING ON UNSTRUCTURED CHANGING TERRAIN - CONTROL SOFTWARE DEVELOPMENT -

Lilik Sutiarso[1], Tomohiro Takigawa[2]

[1]Department of Agricultural Engineering Faculty of Agricultural Technology Universitas Gadjah Mada
[2]Graduate School of Life and Enviromental Sciences University of Tsukuba
E-mail: lilik-soetiarso@ugm.ac.id

ABSTRACT

The control of an autonomous agricultural vehicle operating on unstructured changing terrain includes many objective difficulties. One major difficulty concerns the characteristics of the terrain condition that the vehicle should operate in. Problems ranged from the effects of varying terrain conditions on the autonomous vehicle sensors and traction performance through to the need to deal with the presence of unexpected situations.

On unstructured changing terrain, many factors influence vehicle behavior such as terrain slope, lateral slippage, and so on. Therefore, it is necessary to develop a more suitable model for vehicle motion on these terrain conditions. In order to control the vehicle along a course on unstructured changing terrain, it was developed control software to enable more accurate control. The developed method to control the vehicle when operating on these conditions was Neuro-Fuzzy Controller.

Result of the trained model could be described as follows; number of nodes was 193, number of fuzzy rules was 81, average testing error between simulation and ANFIS output was 0.76, while for experimental and ANFIS output was 1.61. It was concluded that the developed control system had a good accuracy to steer the vehicle.

Keywords: Neuro-Fuzzy Controller, Autonomous Agricultural Vehicle

INTRODUCTION

Neuro-Fuzzy sets and systems constitute one of the most fundamental and influential computational intelligence tools (Jang, 1993). Given the uncertain and incomplete information an autonomous vehicle has about the condition, neuro-fuzzy rules provide an attractive means for mapping sensor data to appropriate control actions in real time. The success of Neuro-Fuzzy Logic Control (NFLC) is owed in a large part to the technology's ability to convert qualitative linguistic descriptions into complex mathematical functions and the ability to deal with various situations without analytical model of the environment (Sadek, 2007; Hellstrom, 2002; Vadekkepat *et al*., 2007). The methodology of the NFLC appears very useful when the processes are too complex for analysis by conventional quantitative techniques or when the available sources of information are interpreted qualitatively, inexactly or uncertainly.

The NFLC is one of intelligent techniques included in the soft computing system (Jang and Sun, 1995). Furthermore, soft computing system is a collection of intelligent techniques working in a complementary way to build robust systems at low cost. Soft computing differs from conventional computing in that, unlike hard computing, these techniques are capable of dealing with imprecision, uncertainty, ambiguity, partial truth, approximation, and optimization issues we usually face in real world problems (Zadeh, 1994). In effect, the role model for soft computing is the human mind. Main advantages of soft computing are: (i) its rich knowledge representation (both at signal and pattern level), (ii) its flexible knowledge acquisition process (including machine learning and learning from human experts), and (iii) its flexible knowledge processing. Soft computing techniques derive their power of generalization from approximating or interpolating to produce outputs from previously unseen inputs by using outputs from previous learned inputs.

Soft computing employs techniques such as; Neural Networks (NN), Fuzzy Logic (FL), Support Vector Machine (SVM), Machine Learning (ML), Evolutionary Computation (EC) and Probabilistic Reasoning (PR), with the latter subsuming belief networks, chaos theory and parts of learning theory, (Wang and Tan, 1997) in a complementary rather than a competitive way. One example of a particularly effective combination is what has come to be known as "neuro-fuzzy (NF) systems". Most NF products are fuzzy rule-based systems in which NN techniques are used for purposes of learning and/or adaption (Zadeh, 1994).

The current trend in intelligent systems or soft computing research is concerned with the integration of artificial intelligent techniques in complementary hybrid framework for solving complex problems. Fuzzy logic offers the important concept of fuzzy set theory, fuzzy if-then rules and approximate reasoning which deals with imprecision and information granularity. Neural networks have on their side the capability for learning and adaptation by adjusting the interconnections between layers.

Furthermore, neuro-fuzzy techniques have emerged from the fusion of Artificial Neural Networks (ANN) and Fuzzy Inference System (FIS) and form a popular framework for solving the real world problems. Moreover, a neuro-fuzzy system is based on a fuzzy system which is trained by a learning algorithm derived from neural network theory.

In a previous research (Sutiarso *et al*., 2002), development of trajectory control system for an autonomous vehicle has been conducted. The developed trajectory control system was implemented for vehicle when approaching a target. Furthermore, in the agricultural operation, the system was experimented for navigating the vehicle to accomplish an automated fertilizer refilling operation (Figure 1).

Fig.1. Autonomous agricultural vehicle

Again, refers to the main research (Sutiarso *et al*., 2002), following four steps were carried out continuously, (i) to develop a trajectory control functions, (ii) to simulate the developed function through computer simulation, (iii) to carry out some preliminary tests, and (iv) to conduct field experiments of the automatic fertilizer refilling operation.

The developed trajectory control system for approaching the target was named a parallel parking system. Mechanism of the vehicle moving can be described as follows, first, the system has to identify a target, then to localize it and finally to steer the vehicle to a target point (TP). In addition, the vehicle aiming at the destination should stay in a correct point for refilling operation (Figure 2).

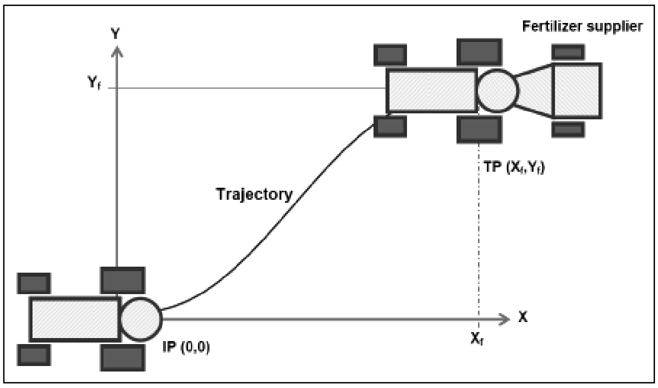

Fig.2. Parallel parking system

First stage of the research, in order to develop the trajectory control function, it was designed the function under open-loop control system circumstance. The function was proposed to steer an autonomous tractor, where vehicle direction angle at an initial position was same value as at a final position i.e. 0^o.

The function must be able to steer a vehicle from a start point to a destination while keeping a favorable trajectory and it should have a simple structure. For this purpose, the function should enable to design the trajectory directly and definitely. Mainly, front-wheel-steering vehicles have two controlling inputs, steering angle and running velocity, but it is difficult to control running speed precisely in agricultural vehicles, for example, due to an unstructured terrain surface.

In a simple field operation, the function was able to steer an autonomous vehicle to approach a facility by following a parallel parking trajectory. Basically, the proposed steering function was developed by using a cosinus function. Whereas, characteristics of a cosinus function is similar to a sinus function. The derived equation for parallel parking model can be described as follows.

$$\tan\delta = l\cos^3\theta\left(\frac{\pi^2 y_f \cos\left(\frac{\pi x}{x_f}\right)}{2x_f^2} + \frac{2a}{x_f^2} + \frac{6bx}{x_f^3} + \frac{12cx^2}{x_f^4} + \frac{20dx^3}{x_f^5}\right)$$

Where, (x_f, y_f) denotes a position of the target object in XY−coordinates, θ_f as the direction angle, δ as vehicle steering angle, and V and l are vehicle running velocity and the wheel base respectively.

When conducting one of series of the preliminary test, particularly, to clarify the trajectory system performance in various kind of terrain surface. As additional information, three kinds of terrain surface were used in the test, i.e. (i) concrete (hard terrain), (ii) grassland and (iii) tilled soil (soft terrain). It was considered that in a real field operation, the vehicle pass through on various kinds of terrain surface, for example; start from garage, then go to the field, also when aiming the fertilizer refiller machine (box) as a target point.

Actually, the objective of the test was to investigate an accuracy of the system performance due to an effect of various kinds of terrain surface (surface slip).

Derived from a field experiment, it was reported that under real conditions, the simulated trajectory function could not be followed exactly. However, their trajectory curves were reasonably similar to the simulated curve (see Figure 3). Due to some external disturbances such as wheel slip effect for different terrain surfaces, when the vehicle followed the trajectory path, that is, for the target point of (5m,1m), there were no significant differences among the three surface types, and positioning error was up to 1% or 1 cm. However, for the target point of (5m,2m), the error of 4% or 8 cm that occurred on the soil surface was larger than others as predicted based on the lateral distance with wheel slip of up to 25%.

Based on the problem that occurred in the field operation, decreasing of the performance accuracy was up to 8 cm (4%) due mainly to surface slip as 25% at tilled soil surface. Thus, it can be concluded that kind of terrain surface is siginificantly to have influence on accuracy level of the trajectory control performance (Figure 3).

In order to overcome the problem, the research was conducted for improving the developed trajectory control function, particularly when operating in various kind of terrain surface. One of a mathematical technique related to develop the control system, that named “neuro-fuzzy” system was inputted to the main function.

As hyphothesis, result of the research, performance of the trajectory function should be improved to navigate the vehilcle when operating in some kinds of terrain surface. To graphically illustrate the dynamic of vehicle steering angle as control input, it was used a software package i.e. Matlab language of technical computing.

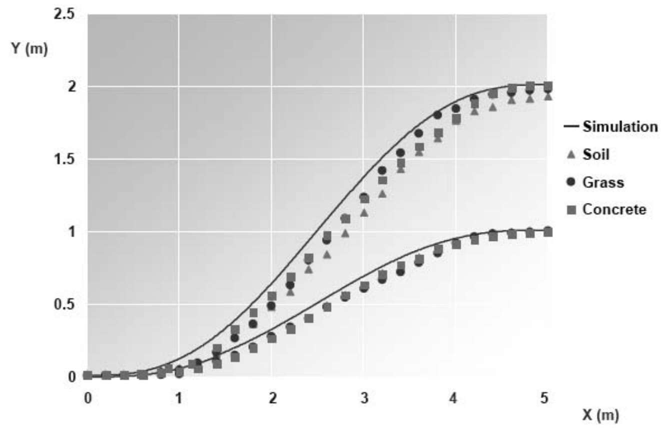

Fig. 3. Experimental trajectory of the vehicle in three kinds of terrain surface

METHODOLOGY

In a following research, it was carried out three steps in order to develop a NFLC based parallel parking trajectory model for navigating an autonomous agricultural vehicle, that were; (i) selecting input - output variables of the system, (ii) collecting input-output experimental data from the real system, and (iii) training the developed model.

Refers to previous descriptions regarding the parallel parking trajectory model, it is selected parameters that related to the model which categorized into a system input as well as output. Input is steering angle while, outputs are vehicle position, and vehicle’s direction angle, where all variables are time-variant function.

In order to be well suited for solving the problems, it was focused only one of the techniques, i.e. an adaptive neuro-fuzzy inference system (ANFIS).

Moreover detailed, a fuzzy inference system (FIS) is also known as fuzzy-rule-based system, fuzzy models, fuzzy associative memories (FAM), or fuzzy controllers when used as controllers. Basically a fuzzy inference system is composed of five functional blocks (see Fig. 4).

- a rule base containing a number of fuzzy if-then rules;
- a database which defines the membership functions of the fuzzy sets used in the fuzzy rules;
- a fuzzy inference engines which performs the inference operations on the rules;
- a fuzzification interface which transforms the crisp inputs into degrees of match with linguistic values;
- a defuzzification interface which transform the fuzzy results of the inference into a crisp output.

Usually, the rule base and the database are jointly referred to as the knowledge base.

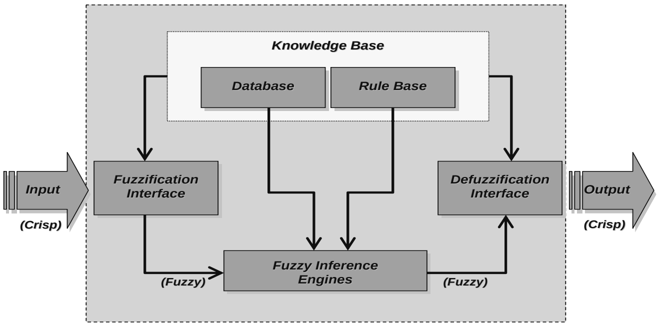

Fig. 4. Fuzzy inference system - fuzzy controller

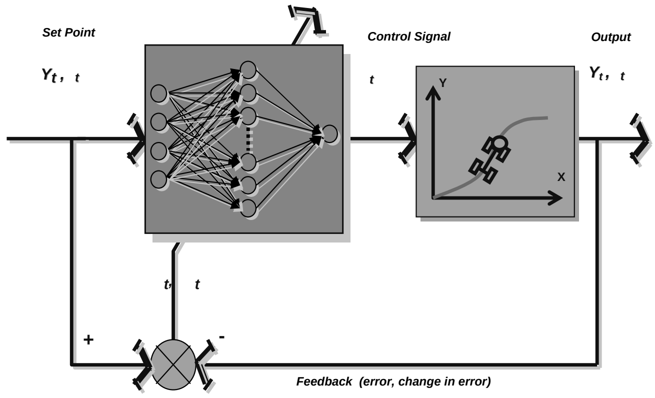

Fig. 6. Block diagram of neuro-fuzzy based trajectory control system

RESULTS AND DISCUSSION

As described before, it was carried out three steps in order to develop a NFLC based parallel parking trajectory model for navigating an autonomous agricultural vehicle, that were; (i) selecting input - output variables of the system, (ii) collecting input-output experimental data from the real system, and (iii) training ANFIS model

Moreover, in detail, three steps of the research were described as follows.

1. Selecting input - output variables of the system

Refers to the previous descriptions regarding the parallel parking trajectory model and particularly, it was selected parameters that related to the model which categorized into a system input as well as output. Input is steering angle $\delta(t)$ while, outputs are vehicle position $y(t)$, and vehicle's direction angle $\theta(t)$, where all variables are time-variant function. To make this description clearly, the following figure is shown a simple block diagram of the system (Fig. 5.).

Based on the system (Fig. 5), it was constructed a control system structure that suitable for being applied to ANFIS architecture, and ready to perform Fuzzy Inference System (FIS) analysis (Fig. 6 and Fig. 7). Thus, in the new structure, there were four input variables and one output variable. Input variables were (i) error of $y(t)$, (ii) change in error of $y(t)$, (iii) error of $\theta(t)$, and change in error of $\theta(t)$, while output variable was steering angle $\delta(t)$.

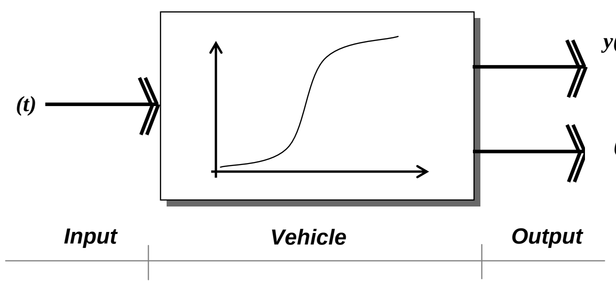

Fig. 5. Simple block diagram of the trajectory control system

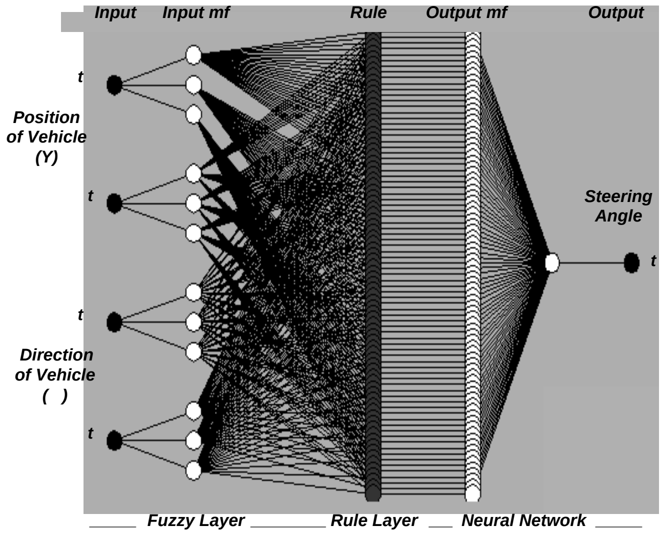

Fig. 7. Structure of ANFIS for the trajectory control system

2. Collecting input - output experimental data from the real system

Collecting input-output experimental data from the system was conducted previously in various terrain surfaces, such as; tilled soil, grassland and concrete. By using the parallel parking trajectory model, the vehicle was operated to approach the final target that locate at (5m,1m) and (5m,2m), and the results is shown in Fig. 3.

3. Training ANFIS model

For training ANFIS Model, several steps were conducted by used a Matlab - the Language of Technical Computing version 7.0.1. In the followings, it was captured the results of training ANFIS model.

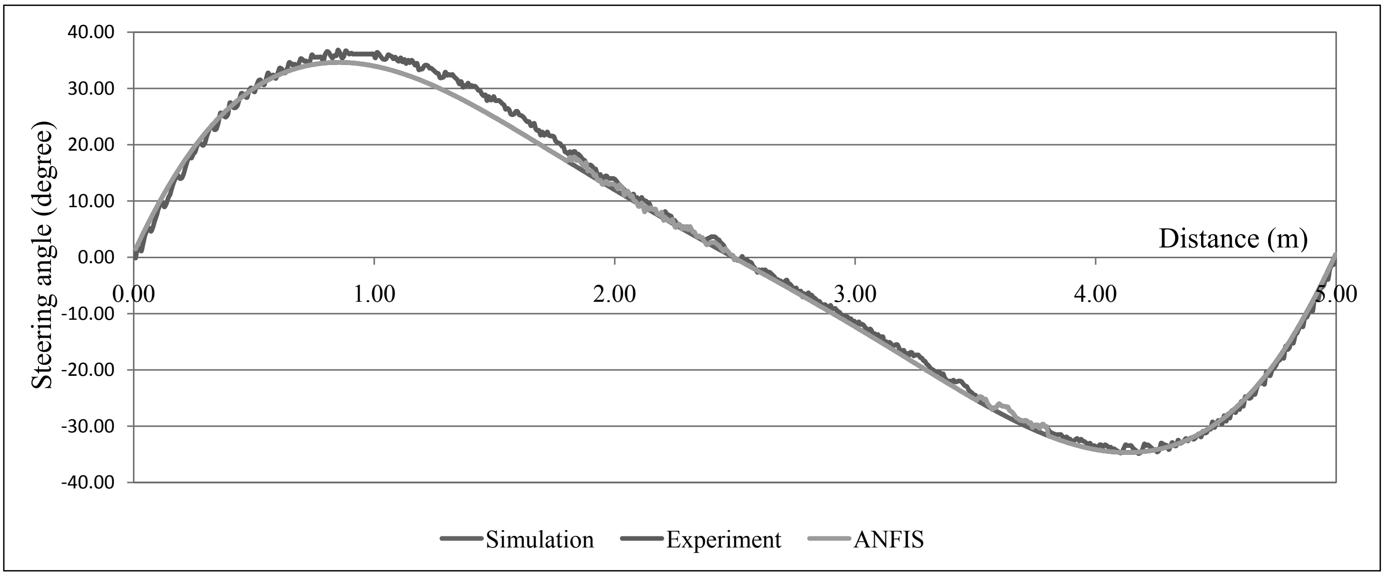

Fig. 8. Comparing simulation, experimental and ANFIS output

The result of the training model can be described as follows; (i) number of nodes is 193, (ii) total number of parameters is 429, (iii) number of training and checking data pairs is 690, (iv) number of fuzzy rules is 81, (v) average testing error between desired output and ANFIS output is 0.76 and (vi) average testing error between experimental output and ANFIS output is 1.61.

CONCLUSIONS

As concluded, after the experimental data was trained by using ANFIS method, it was obtained advantages of improving performance of the system by minimizing the error.

Based on this research, that focused on improving performance of the trajectory control system by introducing a neuro-fuzzy logic controllers system (NFLC), the next research, to conduct a field experiment for validating the new control system. Also, it will be considered, for overcoming the wheel slippage problems due to unstructured terrain surfaces, it may be added one more input signal i.e. a vehicle running velocity as time-variant function.

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