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The Ways of Fuzzy Control Algorithms Using for Harvesting Machines Tracking

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Abstract

This contribution is oriented to ways of a fuzzy regulation using for machine tracking of the harvest machines. The main aim of this work was to practice verify and evaluate of functionality of control fuzzy algorithms for an Ackerman's chassis which are generally used in agriculture machines for the crops harvesting. Design of the fuzzy control algorithm was focused to the wall following algorithm and obstacle avoidance. To achieve of the reliable results was made the real model of vehicle with Ackerman's chassis type, which was controlled by PC with using development board Stellaris LM3S8962 based on ARM processor. Fuzzy control algorithms were developed in LabView application. Deviations were up to 0.2 m, which can be reduced to 0.1 m by hardware changing.

Key words

Fuzzy control, algorithm, Ackerman, tracking automation, harvest.

Introduction

The important aspect of agricultural crops harvesting is speed and accuracy. With higher motion speed of the agricultural machine, the result productivity and work efficiency will be higher. Higher rate disproportionately increases the mental load of worker that may adversely affects to total concentration. Increasing the speed of harvesting, and decreasing mental work of the worker at the same time, could be workable with using automation tracking control. Psychical load reducing extends work time, time to exhaustion and inattention of the worker. Steering person will have more free time that he can uses for setting of the cutting deck and optimizing acquisition parameters during driving. The driver's work is simplified in poor visibility too and the harvesting machine performance remains stable. Parameters such as tolerance, scale and agility utilized in data sampling for using in precision agriculture required an expressive number of researches and development of techniques and instruments for automation (Tabile, 2011). New technologies and devices for real-time data acquisition and actuation have been released to equip agricultural machinery to support and automate these practices (Stone et al., 2008). What is more, higher safety of the autonomous driving of the agricultural machine is needed as Murakami et al. (2008) developed and described. However, since the agricultural environment is complex and loosely structured fundamental technologies must be developed to solve difficult problems such as: mobile operation in tree-dimensional continuously changing track random location of targets which are difficult to detect and reach (hidden leaves and positioned among branches) variability in fruit size and shape delicate products and hostile environmental conditions like dust, dirt and extreme temperature and humidity (Edan, 1995).

Materials and methods

Agriculture areas contain obstacles. Usually, masts, poles and various objects, which are essential to the safe operation unwanted. These barriers is necessary avoid and keep minimum distance for maximum harvest. Area is changing dynamically from the aspect of the harvesting device. Mathematical description of the regulatory (control) system for such an environment is very difficult, sometimes impracticable.

Chassis mobility is another key factor in the agriculture machinery control. It specifies the number of differential degrees of freedom of a chassis (DDOF). Agricultural machines are generally designed on the Ackerman's chassis type with one of degree of freedom and one rotation axis with a limited range of angles. It follows that is not able to rotate around its axis. Control algorithm for smooth system control and Ackerman's chassis is more complex.

A sufficient sensor count is necessary to provide a suitable basis for input information base. These sensors will be used to obtain primary input data for control process of autonomous system and for avoiding obstacles. Measurements obtained from various sensors are analogue values (not precisely defined), so there is difficult to make decision during control process. In contrast, output actuators' values of driven system must be precisely defined (called as sharp control values). In case of information feedback of control process, it is possible to use the advantages of inertial navigation, because the information about the position could be obtained through the acceleration and gyro data from accelerometers and gyroscopes (Cviklovič, Hrubý, 2011).

The above description is a summary of the requirements, which can be fulfilled by an appropriate control algorithm. One of the ways is using fuzzy control algorithm. Fuzzy control is qualitative control based on qualitative description of real systems. We do not need to know the exact equation of control system. One of main benefits of fuzzy logic system is intuitiveness of design, that allows control system designing too, where isn't available a mathematical model of the system or it is hardly determinable (Hrubý, 2007). The advantage of fuzzy control versus conventional methods is the ability to synchronous control of multiple independent physical variables (Cviklovič, 2011).

Characteristic feature of fuzzy control is the possibility of immediate use posteriori knowledge about human controlled process, which we refer to as base of data. Base of data consist information about the invariant states and the intervals where input and output variables with their limits move. The most important segments of base of data are verbally defined control rules by which are written up the complex control algorithm of the system.

The fuzzy controller's block diagram consists of fuzzyfication module where all input values are normalized. Next, normalized values are assigned to fuzzy sets of membership functions through input membership functions. These membership functions determine the degree how the measured value belongs to the fuzzy set. Memberships (u_i) can take values from 0 (element is not in set) to 1 (element belongs set).

Fuzzy sets are described by linguistic variables that could be any expression of any language. For example, a fuzzy set "distance from obstacle" contains the linguistic variables *{Near (N), Middle (M), Far (F)}*. Implemented verbal quantification of distance from obstacle (e.g. "Near") that refers to diffused fuzzy set defined by the characteristic function of membership. Examples of three input fuzzy membership functions that are represented by linguistic variables are shown in Figure 2.

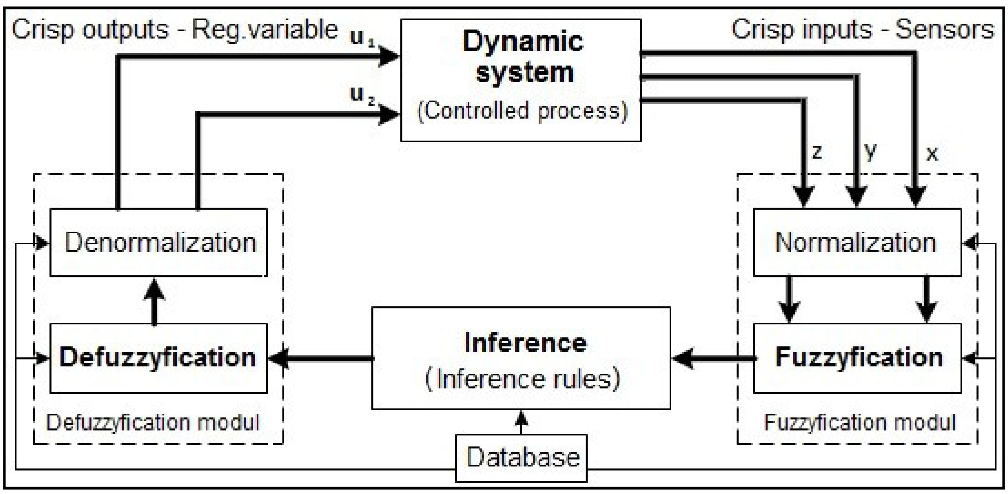

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Figure 1: Block diagram of fuzzy regulation process for three input variables and two output actuators.

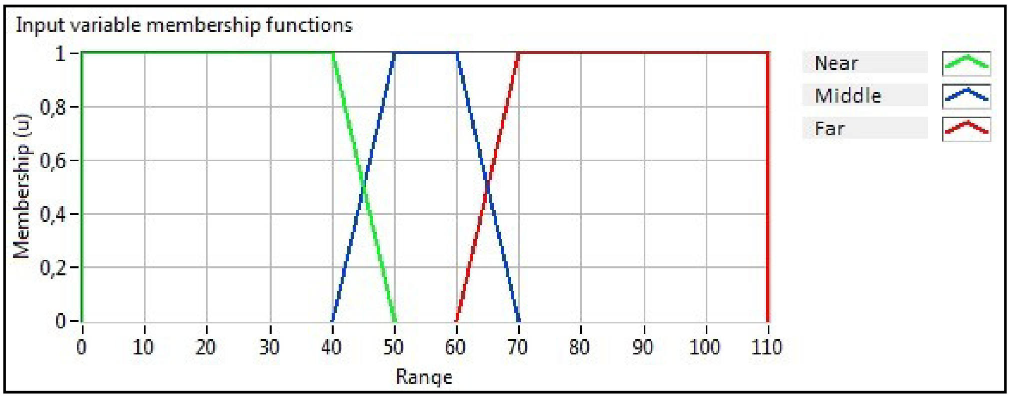

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Figure 2: Input functions of membership for input variable "x" is represented by linguistic variables "Near" (N), "Middle" (M) and "Far" (F).

In the block of inference is realized inference mechanism which uses the knowledge base of decision rules (interference rules) and fuzzyficated values. Output fuzzy sets are created of them. For automated control of agricultural machinery, fuzzy algorithm controls three input variables x, y, z for two actuating variables u_1, u_2. That is characterized by a number of fuzzy sets, which are represented by linguistic variables. The method of obtaining input fuzzy sets is as follow (Modrlák, 2002):

$$\alpha_1 = m_N(x) \wedge m_N(y) \wedge m_N(z) = \min\{m_N(x), m_N(y), m_N(z)\} \quad (1)$$

$$\alpha_2 = m_M(x) \wedge m_M(y) \wedge m_M(z) = \min\{m_M(x), m_M(y), m_M(z)\} \quad (2)$$

where:

α_1 is degree of membership function $m_N(u_1)$ of linguistic variable *N* of actuating variable u_1

α_2 is degree of membership function $m_M(u_2)$ of linguistic variable *M* of actuating variable u_1

$m_N(x)$ is membership function of linguistic variable *N* of input variable *x*

$m_N(y)$ is membership function of linguistic variable *N* of input variable *y*

$m_N(z)$ is membership function of linguistic variable N of input variable *z*

$m_M(x)$ is membership function of linguistic variable *M* of input variable *x*

$m_M(y)$ is membership function of linguistic variable M of input variable *y*

$m_M(z)$ is membership function of linguistic variable *M* of input variable *z*

Fuzzy sets of actuating variables u_1 and u_2 can be determined by cutting of output function of membership according to Mamdani implication:

$$*m_N(u_1) = \alpha_1 \wedge m_N(u_1) = \min\{\alpha_1, m_N(u_1)\} \quad (3)$$

$$*m_M(u_1) = \alpha_2 \wedge m_M(u_1) = \min\{\alpha_2, m_M(u_1)\} \quad (4)$$

$$*m_N(u_2) = \alpha_1 \wedge m_N(u_2) = \min\{\alpha_1, m_N(u_2)\} \quad (5)$$

$$*m_M(u_2) = \alpha_2 \wedge m_M(u_2) = \min\{\alpha_2, m_M(u_2)\} \quad (6)$$

where:

$m_N(u_1)$ is membership function of linguistic variable *N* of actuating variable u_1

$m_M(u_1)$ is membership function of linguistic variable *M* of actuating variable u_1

$m_N(u_2)$ is membership function of linguistic variable *N* of actuating variable u_2

$m_M(u_2)$ is membership function of linguistic variable *M* of actuating variable u_2

$*m_N(u_1)$ is fuzzy set of membership function $m_N(u_1)$

$*m_M(u_1)$ is fuzzy set of membership function $m_M(u_1)$

$*m_N(u_2)$ is fuzzy set of membership function $m_N(u_2)$

$*m_M(u_2)$ is fuzzy set of membership function $m_M(u_2)$

Result fuzzy sets for two outputs $m_{CELK}(u_1)$ and $m_{CELK}(u_2)$ can be determined as:

$$m_{CELK}(u_1) = \max\{*m_N(u_1), *m_M(u_1)\} \quad (7)$$

$$m_{CELK}(u_2) = \max\{*m_N(u_2), *m_M(u_2)\} \quad (8)$$

In the case when some of the measurements x, y, z spans multiple fuzzy sets we get more value degree of membership, which cut of output fuzzy

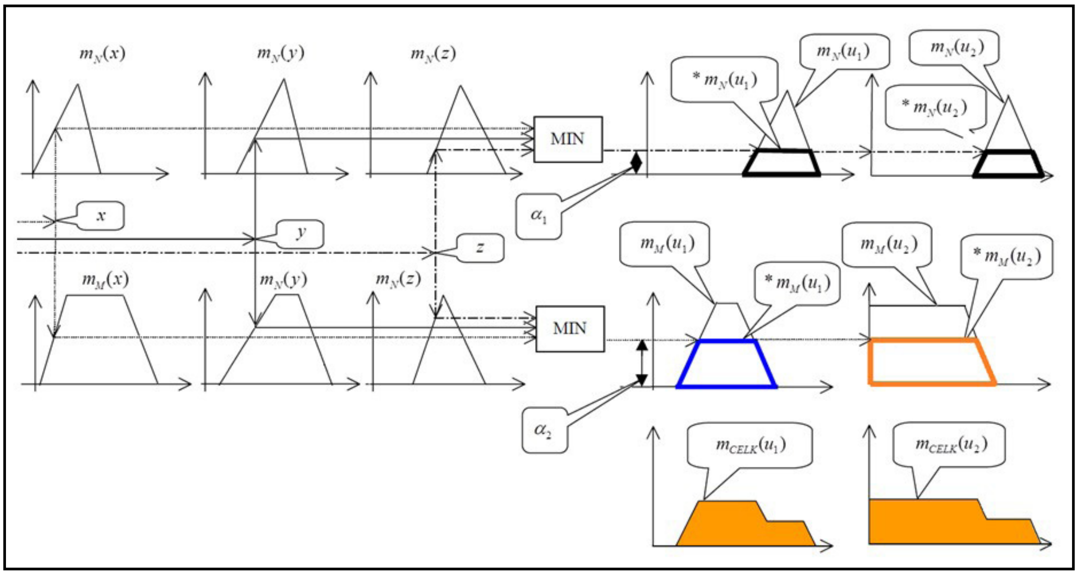

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Figure 3: Graphical representation finding method of output sets $m_{CELK}(u_1)$ a $m_{CELK}(u_2)$

sets $*m_N(u_1)$ and $*m_N(u_2)$. The resulting fuzzy sets of output variables $m_{CELK}(u_1)$ and $m_{CELK}(u_2)$ is given by unification of cutting fuzzy sets. In Figure 3 is shown the way to identify output sets $m_{CELK}(u_1)$ and $m_{CELK}(u_2)$ intervention in the two inference rules with three input variables x, y, z.

The relationships between input and output fuzzy set which are represented by linguistic variables determines the inference rules in the base of rules. Practically it is a simple logical operation that applies quantitatively formulated experience including verbally defined management strategy. With them it is possible to generate the actuating variable.

Decision rules represent body of experiences, knowledge and key information of fuzzy control algorithm. Example of decision rules has the following form:

IF (x belongs to *Near*) **AND** (y belongs to *Near*) **AND** (z belongs to *Near*) **THEN** (u_1 belongs to *Near*) **ALSO** (u_2 belongs to *Near*)

IF (x belongs to *Middle*) **AND** (y belongs to *Near*) **AND** (z belongs to *Near*) **THEN** (u_1 belongs to *Middle*) **ALSO** (u_2 belongs to *Middle*)

The resulting number of decision rules in the base of rules is multiple of input fuzzy sets count. We can write:

$$P = \prod_{i=1}^{n} X_i \tag{9}$$

where:

P is a number interference rules in base of rules,

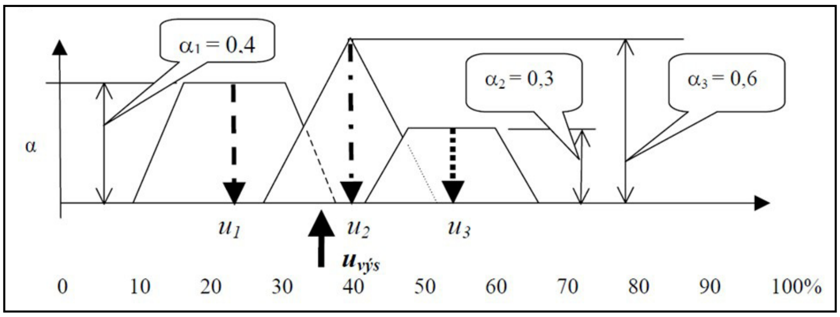
X_i is a number of linguistic values in i-th input variables

n is linguistic variables count.

The output of the interference mechanism is a fuzzy set, but many applications require of sharp value for regulation respectively action hit. The last task of the fuzzy controller performs defuzzyfication module where output fuzzy sets $m_{CELK}(u_1)$ and $m_{CELK}(u_2)$ are assigned to sharp actuating values u_1, u_2. This assignment process is called defuzzyfication.

There are the group of defuzzyfication methods which are based, for example on the method of determining the centre of gravity or method of determining the maximum. Peak search methods are based on determining of most important left (LoM), right (RoM) or in the middle (MoM) of located maximum of the resulting fuzzy sets. These methods "search for maximum" are characterized by high computing performance. On the other hand, the disadvantage is the possibility of discontinuous changes in the output values (Modrlák, 2002).

At the method of determining centre of gravity, the resulting value of action hit is determined as coordinate of the resulting centroid of fuzzy set either as "gravity centre of singletons" (CoM) or as "gravity of surface" (CoG). A centre of maximum method replaces the functional dependence of each



Source: Modrlák, 2002

Figure 4: Calculation of action value using method of determining Centre of Maximum.

sub-output fuzzy set of the typical maximum value (u_i) and sharp output variable ($u_{výs}$) determined as the centre of gravity each fragment values (u_i). Illustration of finding sharp output values $U_{výs}$ according to the method of gravity centre by singletons is shown in Figure 4.

Mathematical equation (10) for finding of the resulting value ($u_{výs}$) of output variable by the "centre of maximum method" is (Modrlák, 2002):

$$u_{výs} = \frac{\sum_{k=1}^{r} \alpha_k * u_k}{\sum_{k=1}^{r} \alpha_k} \qquad (10)$$

where:

$u_{výs}$ is the output value of the output variable

α_k is a value of membership function of the k-th fuzzy set

u_k is a coordinate of the output value of the k-th fuzzy set

The identified sharp values of the output variables after defuzzyfication operation are needed to convert to suitable physical dimension of actuating variable. This operation is named as denormalization.

Result and discussion

Automation homing of agriculture machine requires a good understanding of control mechanism of the chassis. Machinery chassis for harvesting of agriculture crops are generally designed with using Ackerman's principle. Using the Ackerman geometry to trace the front steering angle allows the vehicle to correctly perform a given manoeuvre preserving the minimum level of stability and manoeuvrability (Borrero, 2012). Alignment and keeping the machine at the border of two different height plants (Figure 5b), in conception with Ackerman's chassis, require sophistic solution in terms of control member. In parallel, there is necessary to receive a sufficient number of new information from controlled process, determine and finally transmit the sharp output values to the actuators by the created algorithm. In our case, input information sources were three ultrasound sensors (S1, S2, S3) developed by Maxbotix MaxSonarLV1 placed on real model, as shown in Figure 5a, with two actuators (DC motors). Ultrasound sensors' analogue values discretization, ultrasound sensors synchronization and triggering were realized by ARM microprocessor LM3S8962 with algorithm. DC motors were driven by microprocessor's PWM. Data were transferred to PC via RS232 wireless module. All measurements were processed and analysed using Labview 2010.

Basic requirements that are needed to be implemented in the control algorithm are required distance and parallelism between the longitudinal axis of the agricultural machine and the boundary of two different height plants. This means, the angle between the wall (higher plant in our case) and the longitudinal axis of the machine must be always approach to 0°, respectively, the sums of angles α and β are must be approach to 180° as shown in Figure 5a. This state is achieved when the distance is equal as distance b. Distances between sensor S1 and S2 will be desired value of distance from the wall (Figure 5). Using fuzzy input membership functions were set distance from the wall a = b = 0.55 m and set linguistic value was "Middle" (setpoint distance) in range from 0.5 m to 0.6 m of input linguistic variable as shown in Figure 2.

Instead of the vegetable border crop, in the practical test, a slightly curved wall was used with smaller disparities. There is a presumption to a more

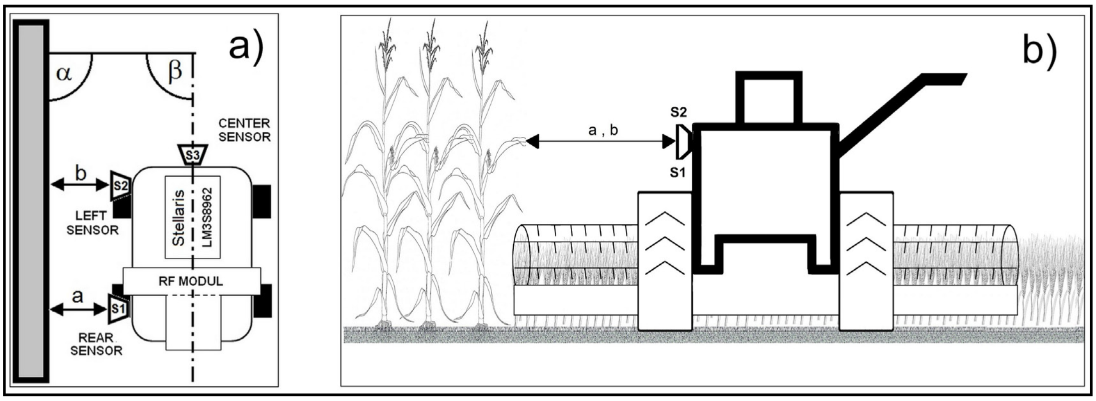


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Figure 5 Illustration of the characteristic parameters for navigate: a) vehicle model beside the wall, b) an agricultural machine at the border crop (e.g. maize).

complex evaluation of the distance measurement from boundary of the adjacent vegetation in an agricultural terrain, due to the indented and not always perfect surfaces (e.g. withered maize leaves). With an additional algorithm focused on random and sudden changes of the measured distances, incorrectly measured distances could be corrected. Accuracy of corrected input values could be increased with establishing a temporary memory, statistical estimation of the measured values and with prediction of these values. Before agricultural machine employment starts in real agriculture terrain, would be necessary to set the threshold sensitivity of abrupt changes of the measured distances for a type of vegetation forming the virtual border.

Distance measuring from obstacles in front of mobile vehicle was provided by ultrasound sensor S3. Distance of manoeuvre start to circumventing obstacles is conditioned with turning radius of the vehicle model. In our case radius was r = 1 m. The limit distance from an obstacle equals to sum of vehicle model rotation radius and desired distance from the wall. This limit was set to fuzzy control algorithm by input membership function for every specified sensor.

The resulting cut of fuzzy sets was created from obtained degrees of membership of input fuzzy set by the Mamdani's implication together with implemented decision rules. Individual rules are set by empirical knowledge, experience and logical reasoning. Sharp values of actuating variables of both outputs were calculated by method of gravity - centre of maximum (CoM).

Action hits in control process was performed by two the electric motors. Output membership functions were chosen in the range from -100 to +100. These numbers represented output (for PWM) power of electric motor in the percentages. Sign means direction of rotation. Fuzzy control surfaces were created on the base of fuzzy control algorithm. The most significant are shown in Figure 6.

Regulatory surfaces determine basic control strategy (Olejár, 2009), which the results are direction changing of vehicle. Horizontal planar surface of yellow square, that is shown in Figure 6a, is defining the required state and steady regulation values on the output. Smaller area means a more precise control and more changes of actuating variable in time. During the practical testing of fuzzy control algorithm for the real model distances were measured by sensor S2 and calculated distances from the wall were saved in the diagram graph 1.

The total straight travelled distance of the vehicle model along the wall was 43 m. Size of deviations was smaller as ± 0.2 m. Such a relatively large variation is caused by delayed mechanical response of control mechanism (mechanical clearances). Real agricultural machines are equipped by hydraulic power steering with electronically controlled hydraulic valves, which would be possible continuous control of the steering mechanism without delay. For example the CAN protocol provides an efficient platform that can be applied for data connection and distributed control of agricultural mobile robots meeting the requirements for an accurate robot movement and an acceptable response time for control commands and supervision (Godoy, 2010). What is more, in real environment the distance measurement by ultrasound sensors can be less precise due

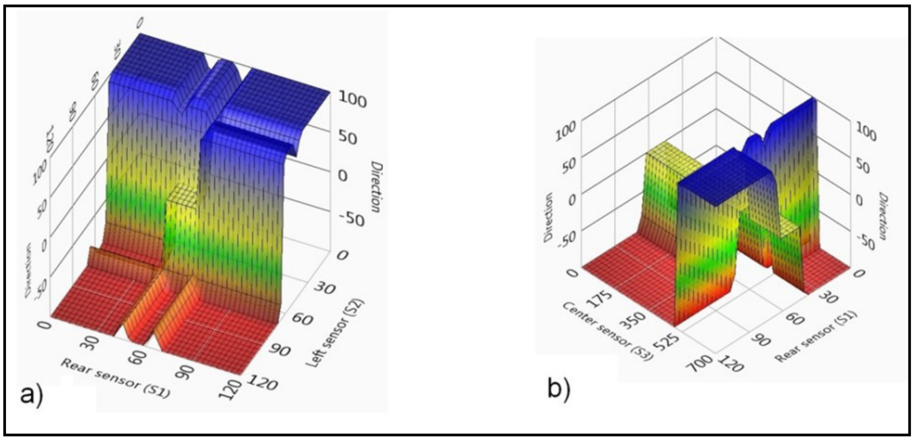

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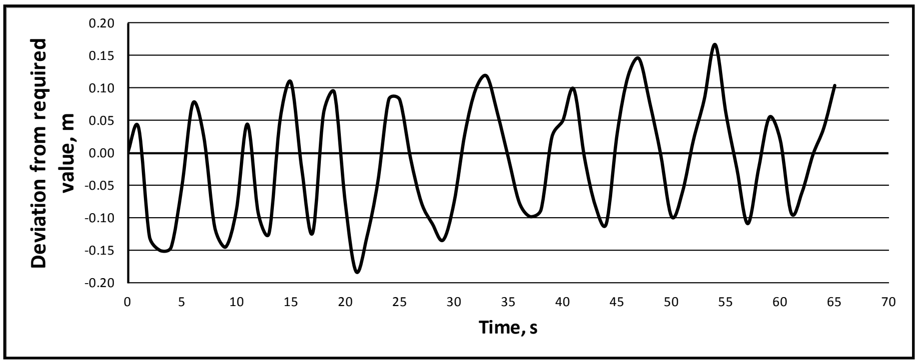
Figure 6: Control surfaces of fuzzy regulator. a) for input variables S1, S2 and output variable “Direction”, b) for input variable S1, S3 and output variable “Direction”.



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Graph 1: Dependence of deviation from the required value in time.

to the characteristics of air such as its temperature, humidity, turbulence and pressure (Kanzel, 2006). Therefore, to increase the steering direction’s accuracy of the harvesting device, an additional gyroscopic sensor can be used with the Cviklovič’s (2012) method of calibration to achieve tolerance of ±0.5 degree.

Fuzzy controller was able to provide responsive reactions up to speed 8m/s. The speed was limited by ultrasound sensors sequential triggering which braked the measuring speed and not sufficient new information were exchanged for fuzzyfication input module.

Defuzzyfication processes are possible speed up and stabilize by using faster methods of distance measuring. The deployment of fuzzy control algorithm to harvesting machines is possible from mechanical as well as electronic point of view. In our case is not usable PID regulator, which principles are better applicable to the one parameter systems (Nagy, 2011, 2012).

Conclusion

The paper describes the knowledge of control sphere and navigation of agricultural machines, which is based on the Ackerman’s chassis type. Using fuzzy control algorithm can streamline works at harvest of agriculture crops of two high different plants. Precision of guidance of the agricultural machine depends equally on the precision of sensors, of the spacing between sensors and of the setting of the input fuzzy membership functions. In our case, the input function of membership was set for linguistic value to “Middle” (i.e. target distance from wall) in range from 0.5m to 0.6m. Using the created fuzzy control algorithm were achieved variations along the guidance of the vehicle model in front of the wall in range ±0.2m, where control mechanism of prototype vehicle model had significant impact. Smaller range of variations could be achieved by using better actuators.

Practical deployment of fuzzy controller, respectively control system, can be in automated management areas with more agricultural machinery, where could be performed parallel activities such as tillage, harvesting beet or spray application. It is also possible to use fuzzy control algorithms together with camera sensors, and create the bases for autonomous lawnmowers, for processing and sorting of agricultural products according to visual properties.

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