COMPOSITION, COORDINATION AND SIMULATION OF REACTIVE FUZZY BEHAVIORS FOR AN MOBILE AGRICULTURAL ROBOT

Rafael V. Sousa
Department of Mechanical Engineering, School of Engineering of São Carlos, University of São Paulo, Av. Trabalhador São-carlense, 400, São Carlos-SP, Brasil.
rafael@cnpdia.embrapa.br

Ricardo Y. Inamasu
Embrapa CNPDIA , Av. XV de Nobrembro, 1452, São Carlos-SP, Brasil.
ricardo@cnpdia.embrapa.br

Arthur J.V. Porto
Department of Mechanical Engineering, School of Engineering of São Carlos, University of São Paulo, Av. Trabalhador São-carlense, 400, São Carlos-SP, Brasil.
ajvporto@sc.usp.br

Daniel Toal
Department of Electronic and Computer Engineering, University of Limerick, Castletroy, Co. Limerick, Ireland.
daniel.toal@ul.ie

Colin Flanagan
Department of Electronic and Computer Engineering, University of Limerick, Castletroy, Co. Limerick, Ireland.
colin.flanagan@ul.ie

Abstract. *The work presents the development of a complex navigational behavior combining some simple fuzzy behaviors for a mobile agricultural robot (MAR). Fuzzy rules are used to compose and coordinate the simple behaviors and an experimental robotic platform based on Khepera mini-robot is proposed to simulate and support the researches on behavior based architecture for agricultural robots. The mini-robot is used for testing of the navigational controller with an integrated perceptual circuit based on light dependent resistors (LDR) to facilitate a path following behavior. Experiments have been performed to evaluate the implemented behaviors and the ability of the platform to operate on a simulated agricultural environment. The results show the feasibility of the approach on the platform and the behaviors that could be used to improve behavior based architectures for MAR's.*

Keywords*: Fuzzy behaviors, behavior based architecture, mobile robot navigation, mobile agricultural robot.*

1. Introduction

The importance of Agribusiness in the worldwide economy, especially in Brasil, is growing as well as the demand of new technologies and methodologies for improving the productivity efficiency. New agricultural practices such as the No-Tillage, Precision Agriculture and practices that take in account environmental protection have been demanded accurate and large sampling scale systems. One of the trends is the application of semi-autonomous or autonomous vehicles and robots on agricultural tasks.

Early developments on AAV (Agricultural Autonomous Vehicle) and MAR (Mobile Agricultural Robot) research are noticed in the UE (Keicher and Seufert, 2000) and countries such as USA (Reid et al., 2000) and Japan (Torri, 2000). Garcia-Alegre et. al, (2001) and Åstrand and Baerveldt (2002), Hague, Southall and Tillett (2002), Darr et. al. (2004) and Bak and Jakobson (2004) are examples of feasible solutions for the development of autonomous agricultural vehicles and robots. However, a limited number of works have been developed reliable systems based on a robotic architectures that are able to perform multiple independent operations and to self-adapt to changing environmental conditions. In other hand, a number of behavior-based architectures have been proposed for mobile robot autonomous navigation in unstructured and/or unexplored environments in other areas. Techniques based on artificial intelligence algorithms, such as fuzzy logic, have been used to implement behavior-based architectures for mobiles robots (Arkin, 1998).

The fuzzy logic theory provides a formal methodology, which can be applied to transfer the human experiences to a robotic system. Linguistic variables are used to compose sets of simple and intuitive conditional statements (fuzzy rules). These heuristic rules associate perceptions to actions generating behaviors for composing architectures to allow robot tasks, such as robot navigation (Seraji and Howard, 2002). Several research works are been focused in the development of methodologies to compose fuzzy behaviors for mobile robots navigation. In Seraji and Howard (2002), the authors show some benefits of using fuzzy logic to compose behavior-based navigation strategy in compare to existing methods based on analytical models. They propose a fuzzy approach for composing behaviors according to the terrain characteristics. The behaviors are integrated through weighting factors, which are adjustable automatically according to the robot navigation context. The experiments are performed not only in an indoor environment but also in an outdoor environment.

A behavior-based architecture developed and implemented on a Khepera basic module robot is discussed in Abreu and Correia (2001). Sub-modules based on fuzzy rules compose the behaviors and activation functions are defined for the behaviors. The physical location of the sensors is used to create the low-level behaviors.

Fuzzy logic approaches are also been proposed for integrating or coordinating low-level behaviors to compose a complex behavior. An approach is described to develop and coordinate behaviors based on fuzzy rules in Saffiotti, Ruspini and Konolige (1999). Contexts of behavior application are defined and fuzzy rules are applied to blend those behaviors. Another approach is presented in Aycard, Charpillet and Haton (1997) where a method to design a fuzzy controller for navigation uses two levels of abstraction. In the first level, the sensors are grouped according to physical location and behaviors are developed for each sensor group. In the second level, the low level behaviors are blended according to an average of the actions or according to a pre-defined behavior hierarchy.

In the work presented here, an approach for implementing a complex navigational behavior is proposed based on two strategies: the composition of simple fuzzy behaviors according to the physical location of the sensors and the integration of these behaviors using fuzzy behavior arbitration. Considering the physical location, three simple behaviors are developed: 'straight in line', 'follow path' and 'avoid obstacles'. The complex navigational behavior is implemented on a platform based on the mini-robot Khepera. A relative localization system is developed based on a robot motion model and odometric measurements for mapping path and evaluating the navigational behavior on a wooden labyrinth and on a simulated agricultural environment.

The paper is organized as follow. The mini-robot platform developed is presented in Section 2, where the relative localization system for path mapping is also described. In Section 3, the methodologies for fuzzy behavior composing and arbitration are described as well as theirs implementation process in the mini-robot platform. The experiments and results are presented and discussed in Section 4. The conclusions are given in Section 5.

2. Khepera-based platform

The platform used in this work has been implemented using the commercial robot Khepera. It includes a Khepera basic module, Khepera IO turret and a perceptual circuit mounted on the IO turret based on VT935G LDR sensors. The LDR sensors are located in front of the bottom circuit board of the base module to read the reflect light by the floor following or looking for a path (dark line). Both LDR sensors are placed side by side, about 4 millimeters distance from the ground and connected to a signal conditioning circuit on the IO turret. The six front infrared (IR) sensors of the basic module are grouped in three pairs of adjacent sensors composing three perception areas: front, left and right. Figure 1 shows a top view of the platform.

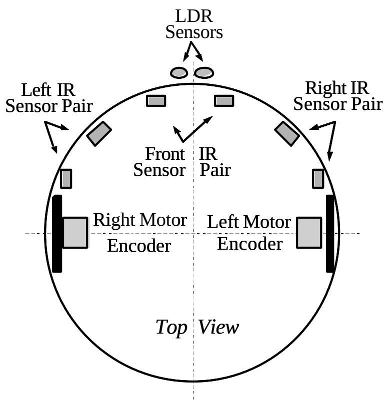

Figure 1. A top view of Khepera-based platform.

All routines are developed and executed on an external PC connected to the Khepera platform by RS232 link operating at 38400 bit/s. Software development is in Labview and Fuzzy Logic Toolkit for Labview, both from National Instruments. Some basic virtual instruments (sub-routines) are available by the Khepera manufacturer and they are used in the routines developed.

2.1. Relative localization system

Both encoders of the Khepera platform are used to supply odometric measurements for the relative localization system. The incremental information (rotational displacements) over the time are integrated by a motion model described in Murata and Hirose (1993) for two wheeled vehicle with differential steering (controlled independently). System Equation (1) calculates the mobile robot position and heading angle integrating the output of incremental encoders.

$$x(\mathrm{k}+1) = x(k) + ds(k)\cdot\cos\left(q\,(k) + \left(dq\,(k)/2\right)\right)$$

$$y(\mathrm{k}+1) = y(k) + ds\,(k)\cdot\sin\left(q\,(k) + \left(dq\,(k)/2\right)\right)$$

$$q\,(k+1) = q\,(k) + d\,q\,(k)$$

$$ds(k) = dD(k)\cdot\left[\sin\left(dq\,(k)/\,2\right)/dq\,(k)/2\right] \tag{1}$$

$$dD(k) = dD_R\,(k) + dD_L\,(k)/2$$

$$dq\,(\,k) = dD_R\,(k) - dD_L\,(k)/w$$

Where:
k: sample instant;
x , y: robot position;
q: robot heading angle;
dq: variations of robot heading angle between the kth and (k+1)th sample instant (sample period);
ds: variations of robot position between the kth and (k+1)th sample instant;
dDR , dDL: displacement of left and right wheels between the kth and (k+1)th sample instant;
w: distance between two drive wheels.

The odometric measurement presents some well-knowing problems that due to accumulative errors as described in Borenstein and Feng (1996). However, the main deal for the experiments is to evaluate the implemented behaviors and the ability of the platform to explore an environment. The main causes the accumulative errors can be controlled for the experiments and the accuracy of the relative localization system is enough for this work. In posterior research works, methods to improve the localization system accuracy could be applied for navigation control based on the odometry, such as sensor fusion (Chung, Ojeda and Borenstein, 2001) .

3. Fuzzy behavior -based control

The perceptual circuit based on LDR pair is used to the 'follow path' behavior for simulating a vision system for identification crop lines. The three groups of IR sensors are used to implement the 'avoid obstacle' based on three related sub-modules defined according to the physical location: 'avoid left obstacle', 'avoid right obstacle' and 'avoid front obstacle'. A deterministic process chooses for executing one of the 'avoid obstacle' sub-modules. A fuzzy arbitrator controller defines the applicability of the 'follow path', 'avoid obstacle' and 'straight in line' for each sample instant (all sensors are read).

3.1. Follow path behavior

A calibration procedure is applied to minimize the effects of different light conditions. Before starting, the navigation, the Khepera platform is placed in two different ways in order to expose the LDR pair to the reflected light by path painted strip (major reading value) and to expose the LDR pair to the reflected light by the cleared floor (minor reading value). The difference between the maximum and the minimum readings define a range for the readings. The crisp input values are calculated based on normalized sensor readings according to the range by the Eq. (2).

$$\mathrm{LDR_S} = \frac{\mathrm{R^S\text{-}R^S_{MIN}}}{\mathrm{R^S_{MAX}\text{-}R^S_{MIN}}} \tag{2}$$

Where:
S: indicates the left or right LDR sensor;
LDR_N: left or right normalized sensor reading;

R: sensor reading during the navigation;
R_{MAX}: major sensor reading in the calibration procedure (path painted strip);
R_{MIN}: minor sensor reading in the calibration procedure (clear floor);

For the LDR pair, two crisp inputs are defined: distance from path (DIST) and difference between the sensor readings (DIF). The crisp values related to the LDR pair are evaluated from Eq. (3) and Eq. (4).

$$\mathrm{DIST}=\min\left(\mathrm{LDR_L},\mathrm{LDR_R}\right) \tag{3}$$

$$\mathrm{DIF}=\mathrm{LDR_L}-\mathrm{LDR_R} \tag{4}$$

The DIST crisp value indicates how distant the LDR pair is becoming out of the path (intensity) and the DIF crisp value denotes which sensor is more distant from the path (direction). The crisp inputs for 'follow path' behavior are composed of three fuzzy terms: far (FAR), medium (MEDIUM) and close (CLOSE) for DIST inputs, and negative (NEG), zero (Z) and positive (POS) for DIF inputs. The behavior outputs are composed of two values obtained by the centroid defuzzyfication method. Both outputs values are referred to each motor, left (L) or right (R). Three fuzzy terms are applied to describe the outputs: forward (F), stop (S) and backward (B). Figure 2 shows the knowledge base for the simple behaviors.

Follow Path

		DIST		
		FAR	MEDIUM	CLOSE
DIF	NEG	F_LB_R	F_LS_R	F_LF_R
	ZERO	S_LS_R	F_LF_R	F_LF_R
	POS	B_LF_R	S_LF_R	F_LF_R

Figure 2. Knowledge base for the 'follow path' behavior.

Two fuzzy controllers were developed for the 'follow path', one for each motor driver. The input and output membership functions are implemented with triangular and trapezoidal shapes.

3.2. Avoid obstacle behavior

Two crisp input values, DIF and DIST, are defined for each IR pair grouped according to the 'avoid obstacle' behavior sub-modules. However, the DIST inputs for IR pairs are evaluated through the major value between the IR readings (IRN) instead of the minor value. The DIST value indicates the distance from a detect object and which group is closest from the object (intensity and direction). The DIF values denote which sensor of the group is closer from the object, that means, the free and occupied spaces (direction). Equations (5) and (6) are using to evaluate the crisp values related to the IR pair grouped (G).

$$\mathrm{DIST_G}=\max\left(\mathrm{IR_L^G},\mathrm{IR_R^G}\right) \tag{5}$$

$$\mathrm{DIF_G}=\mathrm{IR_L^G}-\mathrm{IR_R^G} \tag{6}$$

Six fuzzy controllers were developed for implementing the 'avoid obstacle' behavior, two for each sub-module (one each for motor driver). A simple arbitration process applied the major value among the values evaluate from Eq. (5) for choosing which sub-module is operate in the sample instants.

The crisp inputs and outputs were composed applying the same fuzzy terms as 'follow path' behavior. Also, the input and output membership functions are implemented with triangular and trapezoidal shapes and the behavior outputs are obtained by the centroid defuzzyfication method. Figure 3 shows the knowledge base for the 'avoid obstacle' behavior sub-modules.

Avoid Front Obstacle

		DIST		
		FAR	MEDIUM	CLOSE
DIF	NEG	F_LF_R	S_LF_R	B_LF_R
	ZERO	F_LF_R	S_LS_R	B_LB_R
	POS	F_LF_R	F_LS_R	B_LF_R

Avoid Left Obstacle

		DIST		
		FAR	MEDIUM	CLOSE
DIF	NEG	F_LF_R	F_LS_R	S_LB_R
	ZERO	F_LF_R	F_LS_R	F_LB_R
	POS	F_LF_R	F_LF_R	F_LS_R

Avoid Right Obstacle

		DIST		
		FAR	MEDIUM	CLOSE
DIF	NEG	F_LF_R	F_LF_R	S_LF_R
	ZERO	F_LF_R	S_LF_R	B_LF_R
	POS	F_LF_R	S_LF_R	F_LB_R

Figure 3. Knowledge base for the 'avoid obstacle' behavior sub-modules.

3.3. Fuzzy behavior arbitration

Contexts of application for which simple behavior were defined according to the states where the behaviors are competent: obstacle presence, path presence or free way. Equations (3) and (5) are applied to identify those states in the navigation and it was defined the crisp inputs OBSTACLE, for the IR major reading, and PATH for the LDR minor reading. Than, fuzzy rules were created to associate the context to the behaviors and a fuzzy controller were implemented to arbitrate them. The knowledge base for the fuzzy behavior arbitration is presented in Fig. 4.

		OBSTACLE		
		FAR	MEDIUM	CLOSE
PATH	FAR	STRAIGHT	AVOID	AVOID
	MEDIUM	STRAIGHT	AVOID	AVOID
	CLOSE	FOLLOW	FOLLOW	AVOID

Figure 4. Knowledge base for the for the fuzzy behavior arbitration.

The same linguistic terms as used for the behavior composing are defined for crisp inputs for behavior arbitration. The fuzzy terms applied to the outputs are STRAIGHT, FOLLOW and AVOID, related to 'straight in line', 'follow path' and 'avoid obstacle' behaviors respectively. Triangular and trapezoidal shapes are used and the output is obtained by the centroid defuzzyfication method.

The knowledge base presented in Fig. 4 defines a hierarchy where the 'avoid obstacle' behavior has the highest priority, 'follow path' has an intermediary priority and the 'straight in line' has the lowest priority. This hierarchical control structure coordinates the behavior applicability and composes the navigational complex behavior. Figure 5 illustrates the robotic architecture composed by the Khepera platform, the navigational behavior structure and the relative navigation system.

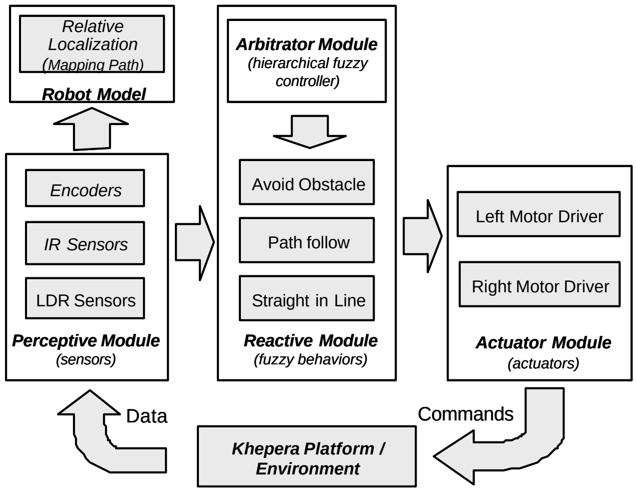

Figure 5. Robotic architecture.

4. Experiments

Different experiments are conduced in a wooden labyrinth for evaluating the abilities of robot exploration, obstacle avoidance and looking for a path to follow. First, a closed path painted strip (dark line) is used to evaluate the follow path behavior. The path was painted on a 0.1-centimeter grid paper (Fig. 6). Others experiments are performed painting a strip in a region of the labyrinth such that part of this strip is very close to a wall to test the arbitration of the behaviors. Different runs are executed starting the robot in different points. The robot navigates without touching the walls and passes around the obstacles without collision (Fig. 7).

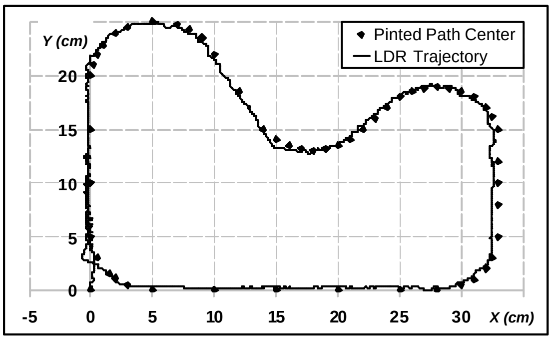

Figure 6. Closed path mapping (based on odometry).

Figure 6 shows a run executed where the robot platform starts the navigation on the (0,0) point and follow the path till complete a lap. The discrete points are real sample points of the closed path collected previously. The continuous line is composed by 2030 sample points acquired based on the motion model. The results show that the robot is able to perform several runs following the strip, which is approximately 0.8 centimeters thick.

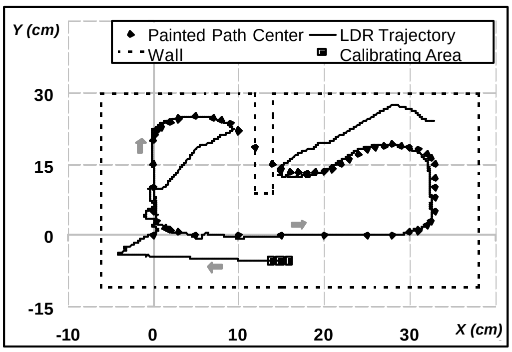

Figure 7. Exploration Path.

Figure 7 shows that when the robot finds the strip, it starts following the strip until the end or until the strip comes closed to the wall. In both situations, the robot restarts its exploration. Positive results have been achieved thus far for speeds up to 25% of rated vehicle maximum speed of the Khepera platform.

A third kind of experiment was carried out on a simulated agricultural environment with three lines of plants (crop lines). One of the deals of the robot on this experiment was navigating based on the orientation of the 'avoid obstacle' behavior and the 'straight in line' without the orientation of spotted lines that would simulate vision system. Thus, the navigation strategy is restricted to straight in line and to self-guide between two lines of plants ("wall plants") oriented by the 'avoid obstacle' recommendations. Some strips were painted only in the end of the lines to guide the robot on the end line maneuver. The results of the experiment shows that the robot architecture allows the robotic platform navigates based on two behaviors only (excepting the maneuver operation) and shows the capacity of the architecture to operate on adverse situations, as losing of a sensorial reference (strip painted). Figure 8 illustrates the experiment and shows a mapping acquired using the relative position system.

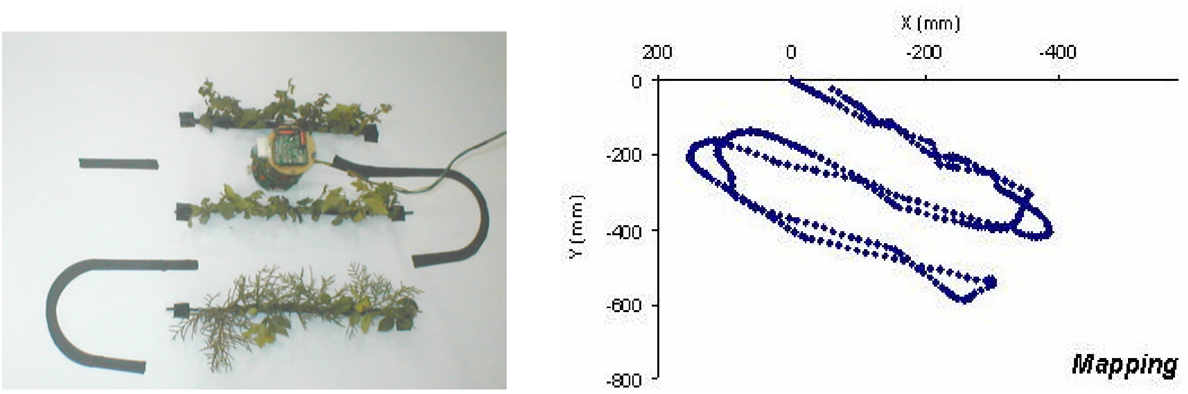

Figure 8. Experiment carried out on a simulated agricultural environment based on three lines of plants

5. Conclusions

Generating simple fuzzy behaviors based in large part on physical sensor location reduces the development complexity of the behavior-based control. The modularization of the architecture by using decentralized fuzzy controllers simplifies the implementation of the robotic architecture and the fuzzy behavior arbitration is an easy and a feasible method to implement the behavior cooperation and compose a complex behavior.

The external processing to control the platform has been shown to be feasible for development. Also, the perceptual circuit based on LDR sensors allows the implementation of a simulate guidance vision system that could be extended and used for tasks such as path mapping.

Some adaptations will be necessary for implementation of the navigational behavior on a real agricultural robot, such as substitute the IR sensor by sonars and the LDR sensors by a vision system for detecting the crop lines. But, the results show the feasibility of the approach on the platform and the behaviors that could be used to improve a behavior based architectures for MAR's.

6. Acknowledgements

This work is supported by a grant from FAPESP (02/0336-8 and 03/06582-0), Brazil, and was carried out in part at the Mobile & Marine Robotics Group at the University of Limerick, Ireland.

7. References

Abreu, A. and Correia, L., 2001, " Fuzzy Behavior-Based Architecture for Decision Control in Autonomous Vehicles", 2001 IEEE Joint International Conference on Control Applications (CCA) & International Symposium on Intelligent Control (ISIC), Mexico-City, Mexico, Sep. 5-7.

Arkin, R.C., 1998, "Behavior-Based Robotics", MIT Press, CA.

Åstrand, B. and Baerveldt A.J., 2002, "An Agricultural Mobile Robot with Vision-Based Perception for Mechanical Weed Control", Autonomous Robots, 13, pp. 21-35.

Aycard, O., Charpillet, F. and Haton, J., 1997, "A new approach to design fuzzy controllers for mobile robots navigation", In IEEE International Symposium on Computational Intelligence in Robotics and Automation - CIRA'97. (Monterey, CA, USA), IEEE Computer Society Press, pp. 68-73.

Bak, T. and Jakobson, H., 2004, “Agricultural Robotic Platform with Four Wheel Steering for Weed Detection”, Biosystems Engineering, Vol. 87, No. 2, pp.126-136.

Borenstein, J. and Feng, L., 1996, “Measurement and correction of systematic odometry errors in mobile robots,” IEEE Trans. Robot. Automat., Vol. 12, pp. 869-880.

Chung, H., Ojeda, L. and Borenstein, J.,2001, “Accurate Mobile Robot Dead-reckoning With a Precision-calibrated Fiber Optic Gyroscope”, IEEE Transactions on Robotics and Automation, Vol. 17, No. 1, pp. 80-84.

Darr, M.J, Stombaugh, T.S., Shearer, S.A. and Fulton, J.P., 2004, “CAN-based distributed control for autonomous vehicles”, Proc.of the 2004 ASAE Annual Meeting. Ottawa, Ontario, Canada.

Garcia-Alegre, M.C., Ribeiro, A., Garcia-Perez, L., Martinez, R. and Guinea, D., 2001, “Autonomous robot in agriculture tasks”, Third European Conference on Precision Agriculture, Montpellier, França, pp. 25-30.

Hague,T., Southall, B. and Tillett, N.D., (2002). “An Autonomous Crop Treatment Robot: Part II”, Real Time Implementation, International Journal Robotics Research, Vol. 21, No. 1, pp. 75-85.

Keicher, R. and Seufert, H., 2000, “Automatic guidance for agricultural vehicles in Europe”, Computers and Electronics in Agriculture, Vol. 25, No. 1-2, p. 169-194.

Murata, S. and Hirose, T., 1993, “Onboard Locating System Using Real-Time Image Processing for a Self-Navigation Vehicle”, IEEE Trans. Industrial Electronics, Vol. 40, No. 1, pp. 145-154.

Reid, J.F., Zhang, Q., Noguchi, N. and Dickson, M, 2000, “Agricultural automatic guidance research in North America”, Computers and Electronics in Agriculture, Vol. 25, No. 1-2, pp. 155-167.

Saffiotti, A., Ruspini, E.H. and Konolige, K., 1999, “Using Fuzzy Logic for Mobile Robot Control”. Chapter 5 in H-J. Zimmermann (ed) Practical Applications of Fuzzy Technologies, Handbooks of Fuzzy Sets series, Vol. 6, pp. 185-205. Kluwer Academic, MA.

Seraji, H. and Howard, A., 2002, “Behavior-Based Navigation on Challenging Terrain: A Fuzzy Logic Approach”, IEEE Transactions on Robotics and Automation, Vo. 18, No. 3, pp. 308-321.

Torii, T., 2000, “Research in autonomous agriculture vehicles in Japan”, Computers and Electronics in Agriculture, Vol. 25, No. 1-2, pp. 133-153.

5. Responsibility notice

The authors are the only responsible for the printed material included in this paper.