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SENSOR FUSION USING DEMPSTER-SHAFER THEORY OF EVIDENCE IN AUTONOMOUS ROBOT NAVIGATION

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Abstract. *In this research, an experimental model of an autonomous mobile robot is constructed which is equipped with an embedded PC, microprocessors, cameras, encoders and ultrasonic sensors in order to study on data processing and performance of different control algorithms. However, this part of the research does not include the performance differences of control algorithms.*
Uncertainties in ultrasonic sensors caused by the unpredictable reflection from environments make them less reliable. By applying Dempster - Shafer evidence theory to data from the sensors, it is aimed to have more reliable sensor data. Dempster-Shafer evidence theory is selected because of its advantages over Bayesian theory.

Key words: *Autonomous mobile robots; sensor fusion; sensor systems; microcomputer based control*

1. INTRODUCTION

Translating sensor readings into probabilities and combining these probabilities using Bayes Rule is one of the best known methods which defines the sensor models for the obstacle avoidance problem of autonomous mobile robots (AMR). For localization and map making algorithms, other two most popular models are Dempster-Shafer Theory (DS Theory) and Histogrammic in Motion Planning Algorithm (HIMM), (Murphy, 2000). The Bayesian and Dempster-Shafer methods can be used with any sensor, in special case ultrasonic sensors in this study.

In Bayes Rule of evidence, there are two parts evaluating the space empty or occupied. However in real time applications, although the system has some kind of response from the sensors, there can be some spaces that cannot be classified as occupied or empty because of the unreliability of the readings of the sensors used. In these cases, DS-Theory is preferred (Gören, 2007-I). This is used in this research for the mobile robot to find a path itself as quickly and as reasonable as possible.

In Bayesian Theory, the sum of the probabilities of a space to be occupied and empty is equal to 1, i.e.:

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$$P(occupied) = 1 - P(empty) \tag{1}$$

For the localization problem of AMRs, it is more useful for the robot to have a function that computes the probability that a region is either occupied or empty given a particular sensor reading s [14]. Probabilities of this type are called *conditional probabilities.* $P(H|s)$ is the probability that the condition H has really occurred given a particular sensor reading s, where $H = \{occupied, empty\}$.

Although we need the probability $P(H|s)$, the sensor model represents the probability $P(s|H)$, which gives the probability that the sensor would return the value being considered with the condition given that it was really "*occupied"*. So the Bayes Rule can be given for n multiple observations $s_1, s_2,..., s_n$ as:

$$P(occupied \mid s) = \frac{P(s_1, s_2,.., s_n \mid occupied) \cdot P(occupied)}{P(s_1, s_2,.., s_n \mid occupied) \cdot P(occupied) + P(s_1, s_2,.., s_n \mid empty) \cdot P(empty)} \tag{2}$$

An alternative to the Bayesian theory of evidence is *Dempster-Shafer Theory* which produces results similar to Bayesian theory. It is much newer theory, originating in the work of A.P. Dempster with extensions by Glen Shafer in 1987 (Shafer, 1976). Different than the Bayes' rule, Dempster-Shafer theory represents evidence as *possibilistic* belief function. Possibilistic means that the function represents partial evidence.

Instead of measuring the probability of a proposition, belief functions measure the *belief mass, m*. Each sensor contributes a belief mass of 1, but can distribute that mass to any combination of propositions. A belief function can represent that the sensor has ambiguous reading, that it literally does not know what is out there. The sensor can distribute some of its quanta of belief mass to the proposition that the area is occupied, but it can also mark a portion of its belief mass to being unable to tell if the area is occupied or empty.

For the case of an occupancy grid, the possible subsets of the grid are: {*occupied*}, {*empty*}, {*occupied, empty*}, *Ø.* Belief that an area is {*occupied, empty*} means that it is either occupied or empty.

Let X is universal set and P(X) is the set of all possible subsets of X, including the empty set, $\emptyset$, in other words the power set. The mass of the empty set is zero;

$$m(\phi) = 0 \tag{3}$$

$$1 = \sum_{A \in P(X)} m(A) \tag{4}$$

The mass of a given member of the power set, A, expresses the proportion of all relevant and available evidence that supports the claim that the actual state belongs to A but to no particular subset of A and denoted by , $m(A)$.

From the mass assignments, the upper and lower bounds of a probability interval can be defined. This interval is bounded by two non-additive continuous measures called belief (or support) and plausibility:

$$pl(A) = \sum_{B \mid B \cap A \neq \emptyset} m(B) \tag{5}$$

The sum of all the masses of subsets of the set of interest is the belief of a set and denoted by bel(A).

$$bel(A) = \sum_{B|B \subseteq A} m(B) \tag{6}$$

Whereas the plausibility is the sum of all the masses of the sets that intersect the set of interest:

$$pl(A) = \sum_{B|B \cap A \neq \emptyset} m(B) \tag{7}$$

$$pl(A) = 1 - bel(\overline{A}) \tag{8}$$

Dempster's rule of combination is a generalization of Bayes rule that emphasizes the agreement between multiple sources and ignores all the conflicting evidence through a normalization factor.

$$m_{1,2}(\phi) = 0 \tag{9}$$

$$m_{1,2}(A) = \frac{1}{1-K} \sum_{B \cap C = A \neq \emptyset} m_1(B) m_2(C) \tag{10}$$

$$K = \sum_{B \cap C = \emptyset} m_1(B) m_2(C) \tag{11}$$

In equations (10) and (11), K is a measure of the amount of conflict between the two mass sets whereas the normalization factor (1-K) has the effect of completely ignoring conflict and attributing any mass associated with conflict to the null set.

To have more reliable data from sensors, sometimes sensory data or data derived from sensory data from disparate sources are combined (Yi, et al., 2000, Murphy, 2000). The reason is that resulting information is in some sense more accurate or more dependable than would be possible when these sources were used individually. This is called sensor fusion.

2. Experimental Model and Sensors

2.1. Kinematics of a Mobile Robot

Self-built autonomous mobile robot (AMR) model in this research, which is also a wheel chair, has four wheels those all independent with each other (See Fig. 1). Front wheels are connected to two separated motors so that the autonomous wheeled robot can have more advantages in motion (Muir, 1986). Kinematics model of the robot is studied for a four wheeled, two wheel drive vehicle. In Fig. 2, reference coordinate system, moving coordinate system and velocity variations in respect to instantaneous center of rotation of Autonomous Mobile Robot (AMR) can be seen.

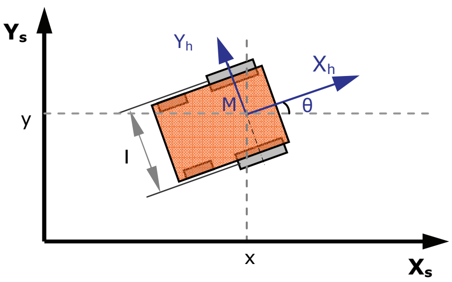
Fig. 1 Experimental autonomous mobile robot.

Mobile robot position with respect to reference coordinates:

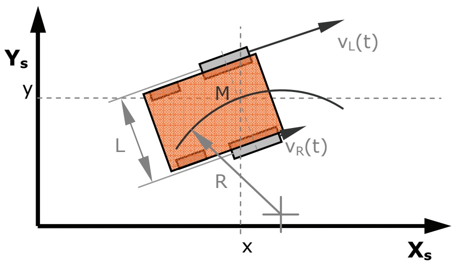
$$q = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \tag{12}$$

Rotation matrix of the reference coordinates with respect to moving coordinate system.

$$R(\theta) = \begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{13}$$



Coordinate system locations
of the mobile robot.



Left and right motor velocities
of the mobile robot.

Fig. 2. Notations and locations of the reference coordinates on the AMR.

Velocities of the right and left wheel:

$$\begin{bmatrix} Vx(t) \\ Vy(t) \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \left(\frac{r}{2}\right) & \left(\frac{r}{2}\right) \\ 0 & 0 \\ -\left(\frac{r}{L}\right) & \left(\frac{r}{L}\right) \end{bmatrix} \cdot \begin{bmatrix} w_L \\ w_R \end{bmatrix} \tag{14}$$

or;

$$\begin{bmatrix} \dot{x}(t) \\ \dot{y}(t) \\ \dot{\theta}(t) \end{bmatrix} = \begin{bmatrix} \cos\theta(t) & 0 \\ \sin\theta(t) & 0 \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} v(t) \\ w(t) \end{bmatrix} \tag{15}$$

In condition of going straight forward (if the velocity of the right and left wheel is equal);

$$w(t)=0 \rightarrow \theta\text{:constant} \tag{16}$$

and

$$v(t)=v_L(t)=v_R(t) \tag{17}$$

If the mobile robot turns around on a point,

$$v(t)=0 \tag{18}$$

$$w(t) = \frac{2}{L} v_R(t) \tag{19}$$

This movement is one of the most known advantages of the dual drive vehicles. In this case, instantaneous center of rotation of the mobile robot model is on the middle of the front axis. And the vehicle can rotate without going forward or backward.

2.2 Ultrasonic Sensors for Navigation

A mobile robot has many sensors on it to know environment, to interact with human and to complete its tasks. For its purposes, obtaining reliable sensor data is as important as having accurate sensor data (Kopacek, 2006). But this is not the whole part, more is necessary for self localization of a mobile robot (Iyengar, 1991). After getting reliable data from sensors, method of evaluation in decision mechanism makes the robot movements either more quick and reasonable or redundant and clumsy. Frequently, more time is spent by robot to know environment than to move towards target. Most suitable method has to be selected rather than more complicated, in means of motion and tasks of the mobile robot. But sometimes, it is inevitable to use more complicated evaluations and algorithms, especially when it is needed to map environment in details. In that case, generally priority level one task is to distinguish meaningful data from data mass.

Six ultrasonic sensors with cone angle of 30^0 are mounted on the model to scan 180 degrees. Two important parameters are effective for this choice. These are: Fast processing to control and reliable measurement data. For ideal 30^0 cone angle, some regions intersect to each other (see Fig. 3). Data from the sensors are taken via microprocessor 1 in Fig. 5*,* whereas second processor is used to get information from self-built encoders on wheels. Dempster – Shafer evidence theory helps to have reliable data from ultrasonic sensors which are roughly illustrated in Fig. 3. Characteristics of the ultrasonic sensors can be seen in Fig. 3.

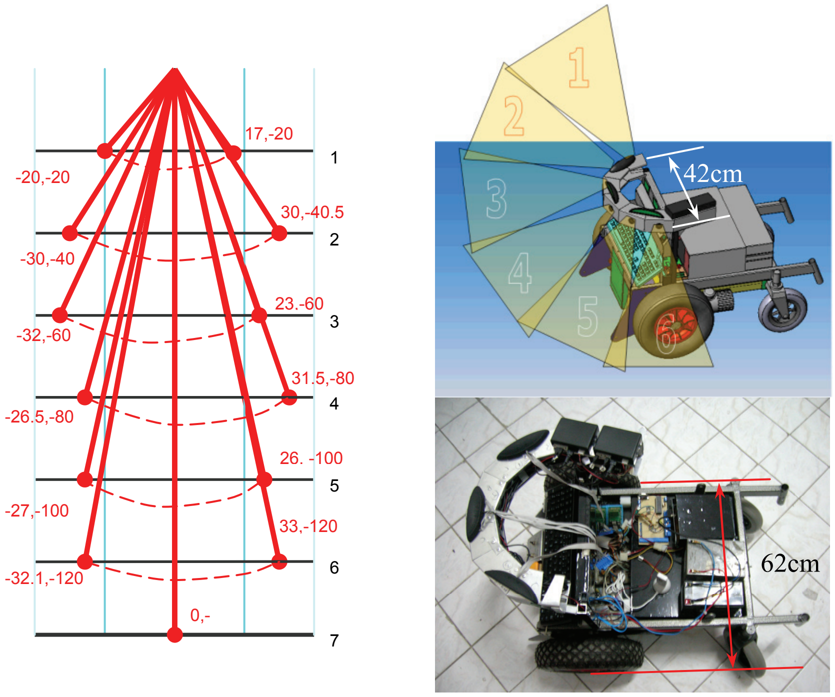


Fig. 3 Characteristics and installation of the ultrasonic sensors.

3. Experiments

3.1 Control of the System

In many researches, mapping algorithms are tested for having knowledge of the environment (Beckerman, 1990; Awad, 2004). However, in this research focus is on more reliable data from sensors aiming the movement of the mobile robot quick and reasonable.

Let a discontinuous curve be denoted as Type 0. A continuous curve whose tangent direction is discontinuous is called Type 1. The set of continuous curves whose tangent direction is also continuous is Type 2. A curve has curvature continuity as well as tangent direction continuity is called Type 3.

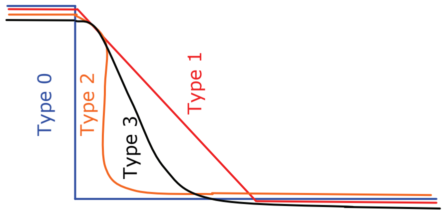


Fig. 4 Smoothness of curves of different types.

Third type curves are considered “smoother” than the previous classes (See Fig. 4). This type curve is said to be optimal motion for a mobile robot. Performance of the control algorithms and improvement with Dempster – Shafer evidence theory are being tested on this matter. For a mobile robot, it is expected to have continuous, smooth curves in motion. If it is an unknown area, different methods of ANN can be used to achieve this task (Haykin, 1994).

Two different control algorithms and performances are being tested on the mobile robot. As mentioned before, an embedded PC (PC104) with digital and analog I/O’s is mounted on the model for neural networks algorithm whereas two microcontrollers are mounted to test fuzzy logic algorithm. Control block in system block diagram in Fig. 5 is microcontroller 1 block that also demonstrates embedded PC in neural network algorithm experiments. Sensor fusion algorithm is loaded on this microcontroller also. Microcontroller 2 block is a modular unit which interfaces for the self-built encoders with RS232 standard to communicate either with embedded PC or the microcontroller 1.

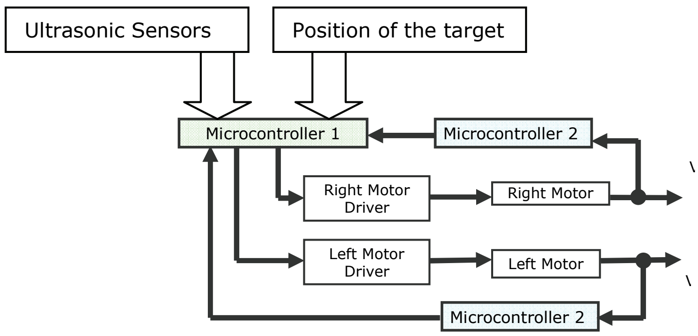


Fig. 5 Control blocks of the mobile robot.

For continuous control of the right and left side motors, equations (20) and (21) are used in algorithm. These equations are also used in forming fuzzy logic algorithm. But, as mentioned before, the results of control of the AMR is not included in this research.

$$V_R = V_{BR} - (S_{VL} \times R_{VL}) \times K_R \tag{20}$$

$$V_L = V_{BL} - (S_{VR} \times R_{VR}) \times K_L \tag{21}$$

V_R : Right motor velocity
V_L : Left motor velocity
V_{BR}: Output Value for Right Motor Max Velocity (for Calibration)
V_{BL}: Output Value for Left Motor Max Velocity (for Calibration)
S_{VL}: Sensor Value for Left (3 for S_3 and S_4, 2 for S_2 and S_5, 1 for S_1 and S_6)
S_{VR}: Sensor Value for Right (3 for S_3 and S_4, 2 for S_2 and S_5, 1 for S_1 and S_6)
R_{VL}: Region Value for left (Closeness factor)
R_{VR}: Region Value for right (Closeness factor)
K_R : Right Motor Velocity Factor
K_L : Left Motor Velocity Factor
X_1 : Closeness Factor for Region 1 (It is close.)
X_2 : Closeness Factor for Region 2 (It is far.)
q_{3x1} : Location matrix for mobile robot.

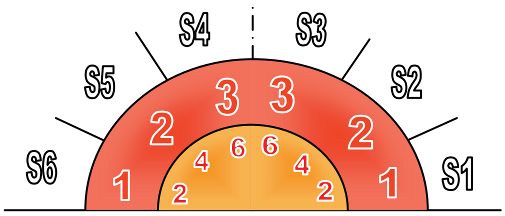


Fig. 6 Regions for the control algorithm.

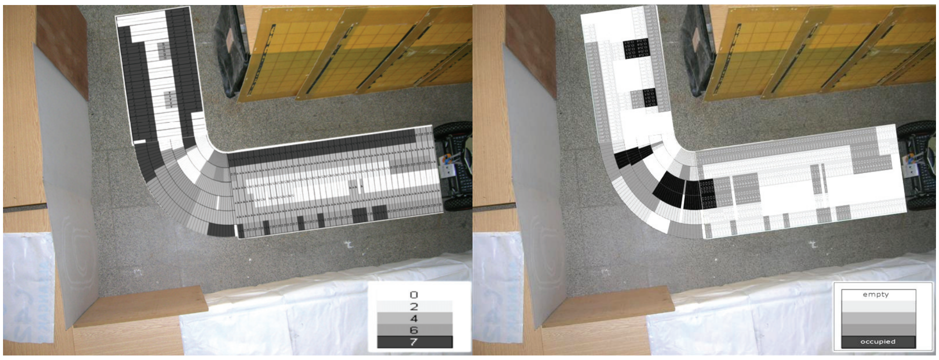
In forming control algorithms of continuous or fuzzy logic, front region of the mobile robot is divided into 12 regions with respect to their closeness probability to unexpected objects and motion direction. With this division, a compact, simple algorithm, so quick motion for AMR is aimed.

Table 1. Sensor Data from Ultrasonic Sensors

	Unprocessed data	Processed data (Bayesian - Occupied)	Processed data (Dempster – Shafer / Occupied)
…	…	…	…
T_n	6,4,6,0,4,6	0.29,0.14,0.79,0.00,0.14,0.29	0.250, 0.339, 0.429, 0.232, 0.143, 0.250
T_{n+1}	6,4,6,0,4,6	0.29,0.14,0.79,0.00,0.14,0.29	0.250, 0.339, 0.429, 0.232, 0.143, 0.250
T_{n+2}	6,4,6,0,4,6	0.29,0.14,0.79,0.00,0.14,0.29	0.250, 0.339, 0.429, 0.232, 0.143, 0.250
T_{n+3}	4,4,6,0,4,6	0.46,0.14,0.79,0.00,0.14,0.29	0.384, 0.384, 0.429, 0.232, 0.143, 0.250
T_{n+}	7,4,6,0,4,6	0.46,0.14,0.79,0.00,0.14,0.29	0.384, 0.384, 0.429, 0.232, 0.143, 0.250
T_{n+5}	7,4,6,0,4,6	0.46,0.14,0.79,0.00,0.14,0.29	0.384, 0.384, 0.429, 0.232, 0.143, 0.250
T_{n+6}	7,4,6,0,4,6	0.46,0.14,0.79,0.00,0.14,0.29	0.384, 0.384, 0.429, 0.232, 0.143, 0.250
T_{n+7}	4,4,6,0,4,6	0.46,0.14,0.79,0.00,0.14,0.29	0.384, 0.384, 0.429, 0.232, 0.143, 0.250
T_{n+8}	4,4,6,0,4,6	0.46,0.14,0.79,0.00,0.14,0.29	0.384, 0.384, 0.429, 0.232, 0.143, 0.250
…	…	…	…

In Table 1, sensor data from ultrasonic sensors and processed data can be seen.

In Fig. 7, unprocessed and processed signals for algorithm during the robot movement are shown respectively. Taking into consideration the dark spaces in Fig. 7, robot behaves quicker and reasonable aiming to find the shortest way to exit. When the robot comes a point that most of the signals are similar in unprocessed signal data, it is easy for it to decide the direction since the processed signal values includes different sensors information in different times using DS Theory. This is not only improves the smoothness of the curve which is shown in Fig. 4, but also decreases the time when achieving the target point.



(a) (b)

Fig. 7 Unprocessed signals from ultrasonic sensors (a) and processed data using DS Theory (b) which are taken during motion of the mobile robot in a corridor.

(a) (b)

Fig. 8 Door – thickness experiment (a), corridor experiment 2 (b).

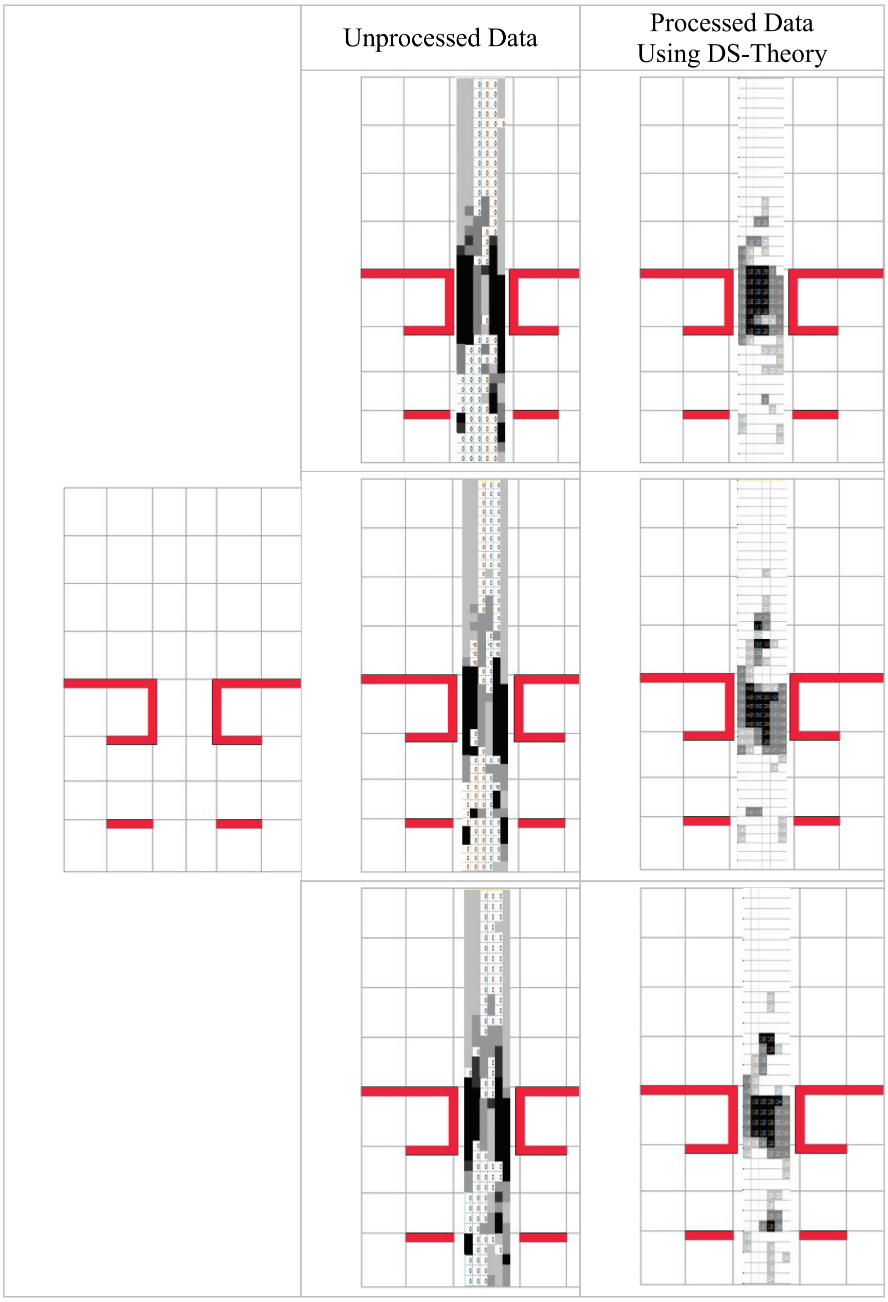


Fig. 9 Door thickness experiment. In this experiment, AMR passes two doors which have different widths.

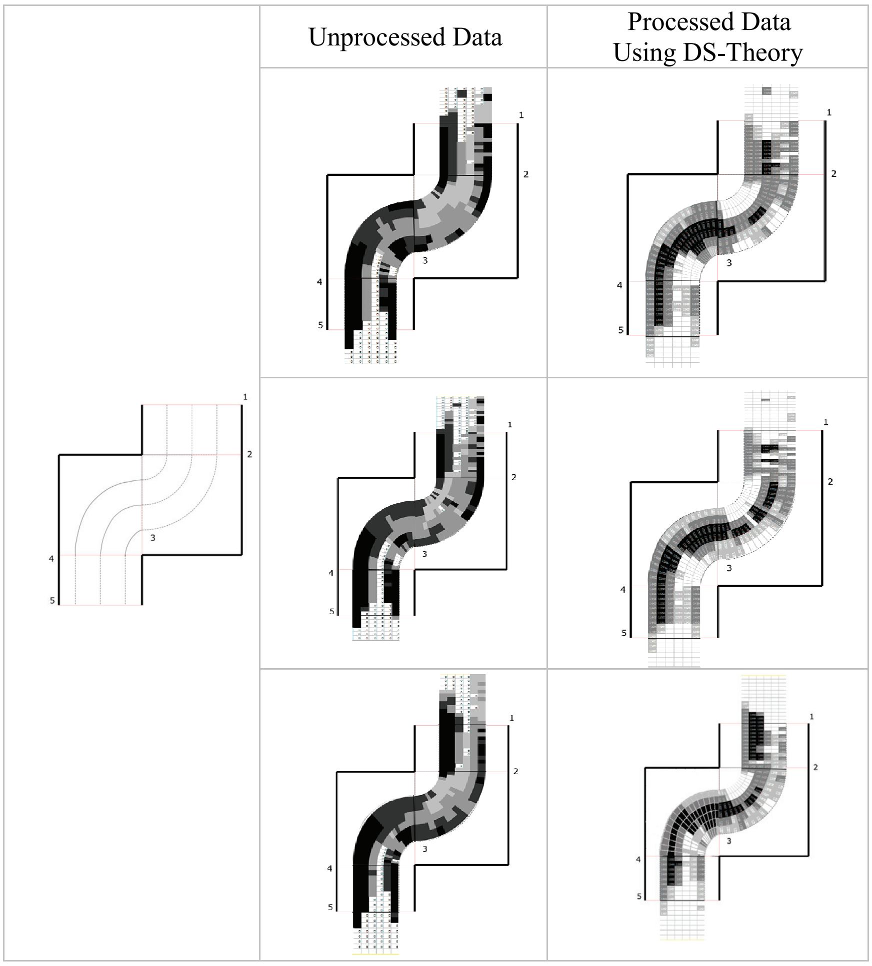


Fig. 10 Corridor experiment. Darker colors show greater sensor data values in scale, i.e. closer walls.

4. Conclusion

Our experiments on different shape and different widths of corridors, and the above results have clearly demonstrated that application of Dempster – Shafer evidence theory improves the reliability of sensor data. The results can be useful for autonomous mobile robots to decide its optimal path to the target. Considering neighbor sensors data in control algorithm not only makes the data more reliable, but also the behavior of AMR's more stable during motion.

DS-Theory gets its advantages for sensor fusion from combining independent sensors data. Therefore, if the full circumference of AMR is covered with the sensors, the data of closeness which are obtained using the side sensors and their neighbors can be also easily comparable with the data which are obtained using the front sensors.

This research project is continuing towards full-scale elaboration do as to employ the full potential of Dempster – Shafer evidence theory.

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FUZIJA SENZORA UPOTREBOM DEMPSTER-ŠAFEROVE TEORIJE EVIDENTNOSTI U NAVIGACIJI AUTONOMNIH ROBOTA

Aytaç Gören, Erol Uyar, Özgün Başer, Zafer Dicle

U ovom istraživanju načinjen je eksperimentalni model autonomnog mobilnog robota koji je opremljen ugradjenim PC-ijem, mikroprocesorima, kamerama, enkoderima i ultrasoničnim senzorima da bi se proučilo procesiranje podataka i performans različitih upravljackim algoritama. Medjutim, ovaj deo istraživanja ne uključuje razlike u performansu upravljackih algoritama. Nepreciznosti u ultrasoničnim senzorima izazvane nepredviljivim reakcijama iz okoline čini ih manje pouzdanima. Koristeći Dempster-Šeferovu teoriju evidentnosti za podatke iz senzora, dobijaju se znatno pouzdaniji podaci iz senzora. Dempster-Šeferova teorija evidentnosti je odabrana zbog prednosti nad Bajesovom statistickom teorijom u sustinskom smislu.

Ključne reči: *Autonomni mobilni roboti, fuzija senzora, sistemi senzora, mikrokompjuterski zasnovana kontrola*