

The Sensing System for the Autonomous Mobile Robot Emmy III

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Abstract — This paper shows the results of the sensing system which was designed for the autonomous mobile robot Emmy III. The proposed Sensing System has as its main part the Paraconsistent Neural Network. This artificial neural network is based on the Paraconsistent Evidential Logics – $E\tau$. The objective of the Sensing System is to inform the other robot components about the obstacle position. The reached results have been satisfactory.

Keywords - Paraconsistent Neural Network; Paraconsistent Logics; Autonomous Mobile Robot; Sensing System.

I. INTRODUCTION

This article describes the Emmy III robot architecture emphasizing the sensing system of the robot [1]. The Emmy III robot is designed to achieve a set point in an environment which is divided into coordinates [2]. The Emmy III robot may be considered as a system divided into three other subsystems: the Planning Subsystem, the Sensing Subsystem and the Mechanical Subsystem.

The Planning Subsystem is responsible for generating the sequence of movements the robot must perform to achieve a set point. The Sensing Subsystem has the objective of informing the Planning Subsystem about the position of obstacles; and the Mechanical Subsystem is the robot itself, it means, the mobile mechanical platform which carries all devices away from the other subsystems. This platform must also perform the sequence of movements which are borne by the Planning Subsystem.

The Planning Subsystem and the Sensing Subsystem have already been implemented, but the Mechanical Subsystem has not been implemented yet.

The Sensing Subsystem uses the Paraconsistent Artificial Neural Network [3] and [4]. This artificial neural network is based on the Paraconsistent Evidential Logics – $E\tau$.

It is described some concepts about the Paraconsistent Evidential Logics – $E\tau$ in the next section.

II. PARACONSISTENT EVIDENTIAL LOGICS

The Paraconsistent Evidential Logics – $E\tau$ [5] is a type of paraconsistent logic in which there may be a Favorable Evidence Degree – μ and a Contrary Evidence Degree – λ in each analyzed sentence.

The Favorable Evidence Degree (μ) is a value between 0 and 1 that represents the favorable evidence in which the sentence is true.

The Contrary Evidence Degree (λ) is a value between 0 and 1 that represents the contrary evidence in which the sentence is true.

Through the Favorable and Contrary Degrees it is possible to represent the four extreme logic states, as shown in the figure 1.

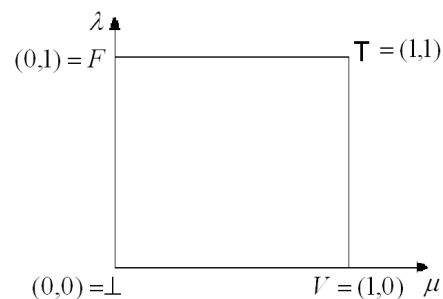


Figure 1. Extreme logic states

The four extreme logic states are:

- True (V)
- False (F)
- Paracomplete ($\perp$)
- Inconsistent (T)

In [6] it is proposed the Paralyzer Algorithm. By this algorithm it is also possible to represent the non-extreme logic state. The figure 2 shows this.

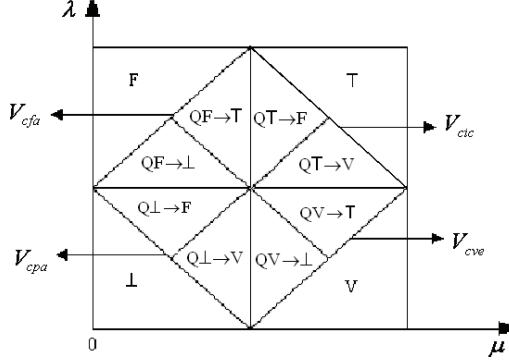


Figure 2. Non extreme logic states

The eight non-extreme logic states are:

- Quasi-true tending to Inconsistent - $QV \rightarrow T$
- Quasi-true tending to Paracomplete - $QV \rightarrow \perp$
- Quasi-false tending to Inconsistent - $QF \rightarrow T$
- Quasi-false tending to Paracomplete - $QF \rightarrow \perp$
- Quasi-inconsistent tending to True - $QT \rightarrow V$
- Quasi-inconsistent tending to False - $QT \rightarrow F$
- Quasi-paracomplete tending to True - $Q\perp \rightarrow V$
- Quasi-paracomplete tending to False - $Q\perp \rightarrow F$

The Uncertainty Degree: $G_{un}(\mu, \lambda) = \mu + \lambda - 1$ and the Certainty Degree: $G_c(\mu, \lambda) = \mu - \lambda$ ($0 \leq \mu, \lambda \leq 1$)

Some additional control values are:

- V_{cic} = maximum value of uncertainty control
- V_{cve} = maximum value of certainty control
- V_{cpa} = minimum value of uncertainty control
- V_{cfa} = minimum value of certainty control

In the next section we describe the proposed sensing system.

III. SENSING SYSTEM

The sensing system is a set of electronic components and softwares responsible for analyzing the environment around the robot and detecting the obstacle positions. After that, it must inform the other components of the robot the position of the obstacles.

The sensing system may get information from any type of sensor. It is shown in this paper a sensing system able to deal with information from just one ultrasonic sensor. But, if there is more than one sensor in the robot, it is possible to build a sensing system similar to the one shown here for each sensor.

In [7] it is presented a method of robot perception and world's modeling that uses a probabilistic tessellated

representation of spatial information called the Occupancy Grid. It is proposed here a similar method, but instead of using probabilistic representation, it is used the Paraconsistent Evidential Logic Et.

The proposed sensing system aims to generate a Favorable Evidence Degree in each environment position. The Favorable Evidence Degree is related to the sentence: there is obstacle in the analyzed position.

The sensing system is divided into two parts. The first part is responsible for receiving the data from the sensors and sending information to the second part of the system. And the second part is the Paraconsistent Artificial Neural Network itself. The figure 3 shows this idea.

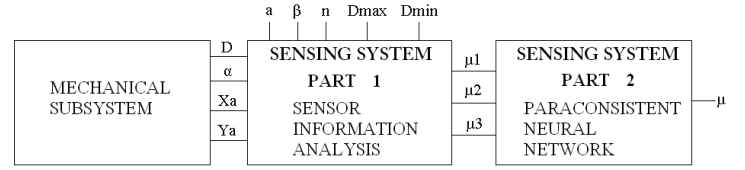


Figure 3. Representation of the sensing system

The proposed sensing system is prepared to receive data from ultrasonic sensors. The robot sensors are on the Mechanical Subsystem. So, this subsystem must treat the data generated by the sensors and send information to the first part of the Sensing Subsystem. The data the Mechanical Subsystem must send to the first part of the Sensing Subsystem are: D, α, Xa and Ya.

- The distance between the sensor and the obstacle (D).
- The angle between the horizontal axis of the environment and the direction to the front of the sensor (α). The figure 4 shows the angle α.

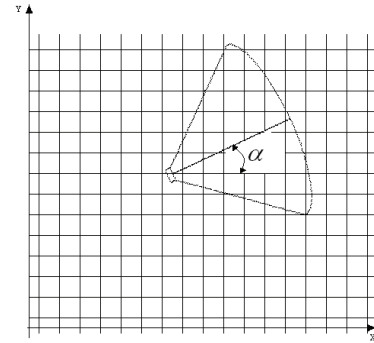


Figure 4. Angle α

- The coordinate where the robot is (Xa, Ya).

In the first part of the Sensing Subsystem there are also some configuration parameters. They are:

- The distance between the environment coordinates (a). The figure 5 shows this.

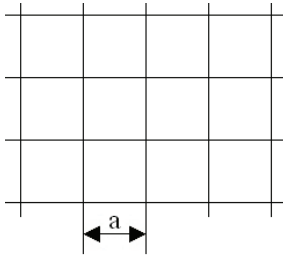


Figure 5. Distance between coordinates

a) The angle of the ultrasonic sensor conical field of view (β). The figure 6 shows this.

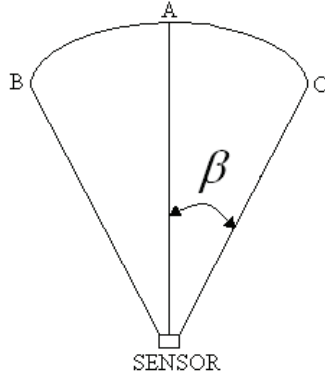


Figure 6. Ultrasonic sensor conical field of view (β)

- a) The number of positions on the arch BC, shown in the figure 6, considered by the system (n).
- b) The maximum distance measured by the sensor which the system considers (D_{max}).
- c) The minimum distance measured by the sensor which the system considers (D_{min}).

The first part of the Sensing System generates three Favorable Evidence Degree, μ_1 , μ_2 and μ_3 .

The Favorable Evidence Degree μ_1 is related to the distance between the sensor and the obstacle. The nearer the obstacle is to the sensor the bigger μ_1 value is.

The Favorable Evidence Degree μ_2 is related to the coordinate position on the arch AC shown in the figure 6. As the analyzed coordinate is near to the point A as bigger is μ_2 value. And as the analyzed coordinate is near to the points A and C, as smaller is the μ_2 value. The inspiration of this idea comes from [8] which says that the probability of the obstacle be near to the point A is high. And this probability decreases as we analyze the region near to the points B and C.

Eventually, the Favorable Evidence Degree μ_3 is the previous value of the coordinate Favorable Evidence Degree.

IV. PARAconsistent ARTIFICIAL NEURAL NETWORK

The Sensing Subsystem neural network of the robot is composed of two types of cells: Analytic Paraconsistent

Artificial Neural Cell – CNAPa and Passage Paraconsistent Artificial Neural Cell - CNAPpa. In the follow it is described the cells.

A. Analytic Paraconsistent Artificial Neural Cell - CNAPa

This cell has two in-puts (μ_{RA} and μ_{RB}) and two out-puts (S1 and S2). Also there are two configuration parameter in-puts (Ftct and Ftc). The figure 7 shows the graphic representation of this cell.

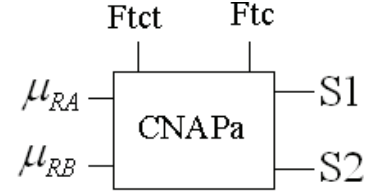


Figure 7. Graphic representation of the Analytic Paraconsistent Artificial Neural Cell

The in-put evidence degrees are:

μ_{RA} , such as: $0 \leq \mu_{RA} \leq 1$

μ_{RB} , such as: $0 \leq \mu_{RB} \leq 1$

There are also two control values:

Contradiction Tolerance Factor – Ft_{ct} , such as: $0 \leq$

$Ft_{ct} \leq 1$

Certainty Tolerance Factor – Ft_c , such as: $0 \leq Ft_c \leq 1$

The Analytic Paraconsistent Artificial Neural Cell – CNAPa has two out-puts. The out-put 1 (S1) is the Resultant Evidence Degree – μ_E .

μ_E , such as: $0 \leq \mu_E \leq 1$

The out-put 2 (S2) is the Resultant Evidence Interval – φ_E .

φ_E , such as: $0 \leq \varphi_E \leq 1$

The Analytic Paraconsistent Artificial Neural Cell calculates the maximum value of certainty - V_{cve} , the minimum value of certainty control - V_{cfa} , the maximum value of uncertainty control - V_{cic} and the minimum value of uncertainty control - V_{cpa} by this way:

$$V_{cve} = \frac{1 + Ft_c}{2} \quad (1)$$

$$V_{cfa} = \frac{1 - Ft_c}{2} \quad (2)$$

$$V_{cic} = \frac{1 + Ft_{ct}}{2} \quad (3)$$

$$V_{cpa} = \frac{1 - Ft_{ct}}{2} \quad (4)$$

The Resultant Evidence Degree – μ_E , is determined in this way:

$$\mu_E = \frac{G_c + 1}{2} \quad (5)$$

As $G_c = \mu - \lambda$:

$$\mu_E = \frac{\mu - \lambda + 1}{2} \quad (6)$$

It is called as Certainty Interval (ϕ) the Certainty Degree interval that can be modified without changing the Uncertainty Degree value. This value is determined in this way.

$$\phi = 1 - |G_{ct}| \quad (7)$$

B. Passage Paraconsistent Artificial Neural Cell - CNAPpa

The Passage Paraconsistent Artificial Neural Cell – CNAPpa has one in-put (μ), one out-put (S1) and one parameter control in-put (Ftc). The figure 8 shows the graphic representation of CNAPpa.

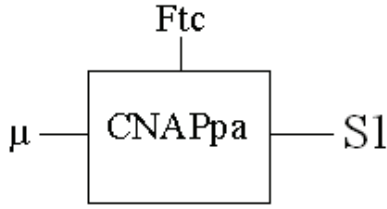


Figure 8. Graphic representation of the Passage Paraconsistent Artificial Neural Cell

The in-put is the Favorable Evidence Degree (μ).

μ , such as: $0 \leq \mu \leq 1$

The value of the out-put S1 is the same as the in-put μ . But, the out-put value may be limited through the parameter control in-put Ftc.

The Passage Paraconsistent Artificial Neural Cell calculates the maximum value of certainty - V_{cve} and the minimum value of certainty control - V_{cfa} by the equations (1) and (2).

It also determines the Resultant Evidence Degree - μ_E by the equation (6). For this, λ is considered as the following.

$$\lambda = 1 - \mu \quad (8)$$

The out-put S1 assumes the same value as in the in-put μ when the follow situation is true:

$$[(V_{cve} \leq \mu_E) \text{ or } (\mu_E \leq V_{cfa})]$$

Otherwise, S1 is 0,5.

C. Paraconsistent Artificial Neural Architecture

It is possible to see in the figure 9 the chosen Paraconsistent Neural Network Architecture for the Sensing Subsystem.

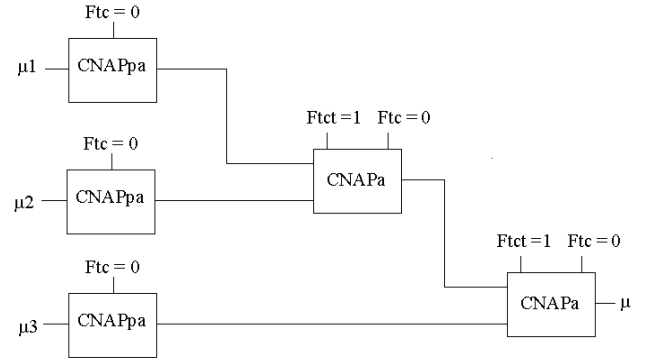


Figure 9. The chosen Paraconsistent Neural Network Architecture for the Sensing System

V. REACHED RESULTS

The Sensing System has been tested by simulating its inputs and analyzing the database generated. The database stores the Favorable Evidence Degree in each environment position analyzed. It is shown here the result of three tests. The information from one ultrasonic sensor was considered as the Sensing System in-puts.

A. First test

The configuration parameters of this test were the following. The distance between the environment coordinates (a): 10. The angle of the ultrasonic sensor conical field of view (β): 30. The number of positions on the arch of the sensor conical field of view considered by the system (n): 10. The maximum distance measured by the sensor which the system considers (Dmax): 800. The minimum distance measured by the sensor which the system considers (Dmin): 8.

The Mechanical Subsystem treats the data from the sensors and generates the Sensing Subsystem in-puts. It was needed to simulate the Sensing Subsystem in-puts because the Mechanical Subsystem has not been implemented yet.

Thus, the simulated Sensing Subsystem data were the ones described in the follow. The distance between the sensor and the obstacle (D): 200. The angle between the horizontal axis of the environment and the direction to the front of the sensor (α): 30. The coordinate where the robot is (X_a, Y_a): (0, 0).

It was simulated the first measuring of the sensor, then, μ_3 initially was 0.

It is shown in the figure 10 the representation of the coordinates in which the Sensing System considered to have obstacles in. Summarizing, the figure 10 is a graphical representation of the database generated by the Sensing Subsystem.

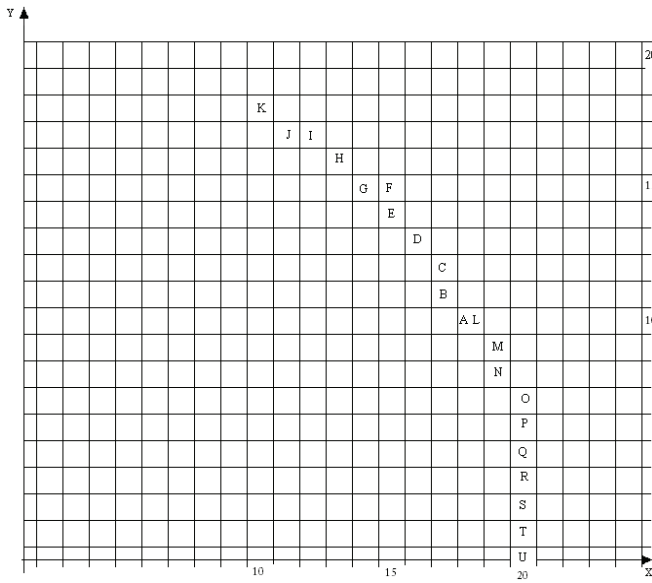


Figure 10. The graphical representation of the database generated by the first test of the Sensing Subsystem.

The analyzed coordinates and their Favorable Evidence Degree are shown in the table 1.

TABLE I. RESULTS OF THE FIRST TEST

Coordinate	μ
A (18,10)	0.438
B (17,11)	0.413
C (17,12)	0.388
D (16,13)	0.363
E (15,14)	0.338
F (15,15)	0.313
G (14,15)	0.288
H (13,16)	0.263
I (12,17)	0.238
J (11,17)	0.213
K (10,18)	0.188
L (18,10)	0.413
M (19,9)	0.388
N (19,8)	0.363
O (20,7)	0.338
P (20,6)	0.313
Q (20,5)	0.288
R (20,4)	0.263
S (20,3)	0.238
T (20,2)	0.213
U (20,0)	0.188

B. Second test

The configuration parameters of this test were the same as the ones from the first test.

The simulated Sensing Subsystem data were the ones described in the follow. The distance between the sensor and the obstacle (D): 400. The angle between the horizontal axis of the environment and the direction to the front of the sensor (α): 45. The coordinate where the robot is (X_a, Y_a): (0, 0).

It was simulated the first measuring of the sensor, then, μ_3

was initially 0.

It is shown in the figure 11 the graphical representation of the database generated by the Sensing Subsystem.

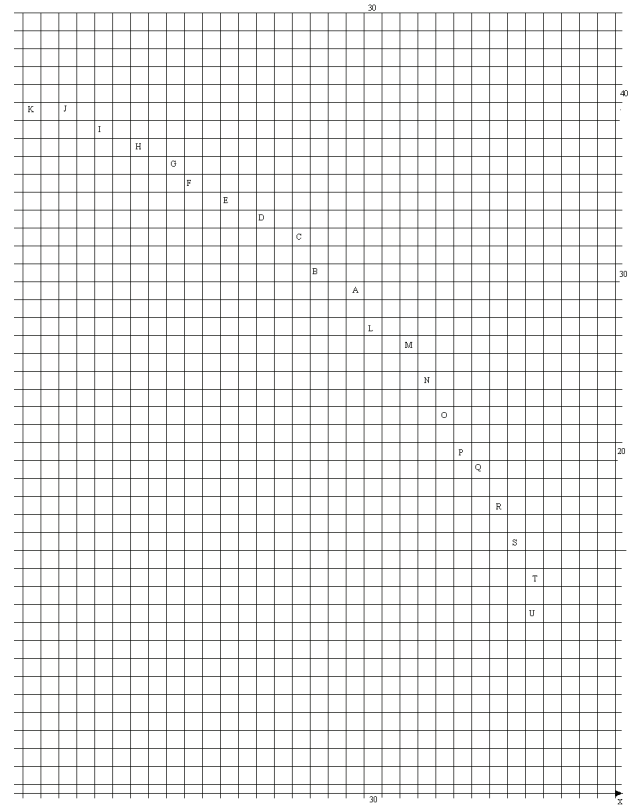


Figure 11. The graphical representation of the database generated by the second test of the Sensing Subsystem

The analyzed coordinates and their Favorable Evidence Degree are shown in the table 2.

TABLE II. RESULTS OF THE SECOND TEST

Coordinate	μ
A (29,29)	0.375
B (27,30)	0.35
C (26,32)	0.325
D (24,33)	0.3
E (22,34)	0.275
F (20,35)	0.25
G (19,36)	0.225
H (17,37)	0.2
I (15,38)	0.175
J (13,39)	0.15
K (11,39)	0.125
L (30,27)	0.35
M (32,26)	0.325
N (33,24)	0.3
O (34,22)	0.275
P (35,20)	0.25
Q (36,19)	0.225
R (37,17)	0.2
S (38,15)	0.175
T (39,13)	0.15
U (39,11)	0.125

C. Third Test

The configuration parameters and the Sensing Subsystem data were the same ones of the second test, then; the analyzed coordinates were the same as the second test. The third test has been done just after the second, therefore, their Favorable Evidence Degree were different from the second test because μ_3 was the Favorable Evidence Degree generated by the second test.

The analyzed coordinates and their Favorable Evidence Degree are shown in the table 3.

TABLE III. RESULTS OF THE THIRD TEST

Coordinate	μ
A (29,29)	0.565
B (27,30)	0.525
C (26,32)	0.49
D (24,33)	0.45
E (22,34)	0.415
F (20,35)	0.375
G (19,36)	0.34
H (17,37)	0.3
I (15,38)	0.265
J (13,39)	0.225
K (11,39)	0.19
L (30,27)	0.525
M (32,26)	0.49
N (33,24)	0.45
O (34,22)	0.415
P (35,20)	0.375
Q (36,19)	0.34
R (37,17)	0.3
S (38,15)	0.265
T (39,13)	0.225
U (39,11)	0.19

If it is considered the sequence of positions from K to U as an arch in the three tests, it is perceived that the Favorable Evidence Degree (μ) decreases as the coordinate is farther distant from the center of the arch. It means that the system is working as desired.

VI. CONCLUSIONS

This paper presents a proposal for the autonomous mobile robot Emmy III. This robot is composed of three modules: Sensing Subsystem, Planning Subsystem and Mechanical Subsystem. The Mechanical Subsystem has not been implemented yet. It is emphasized here the Sensing Subsystem.

The aim of the Sensing Subsystem is to inform the Planning Subsystem about the positions in which obstacles may happen. It considers the environment divided into coordinates.

The Sensing Subsystem is based on the Paraconsistent Artificial Neural Network. The Sensing Subsystem neural network is composed of two types of cells: Analytic Paraconsistent Artificial Neural Cell – CNAPa and Passage Paraconsistent Artificial Neural Cell - CNAPpa.

The out-put of the Sensing Subsystem is the Favorable Evidence Degree related to the statement: there is an obstacle

in the position. In fact, the Sensing Subsystem generates a database with the Favorable Evidence Degree for each analyzed coordinate.

Some tests have been made with the Sensing Subsystem. The reached results are satisfactory.

The next step is the implementation of the Mechanical Subsystem and the connection of the three subsystems.

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