VALIDATION OF A SIMULATED ENVIRONMENT DEVELOPED FOR VALIDATING CFS AUTONOMY

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Abstract: This paper analyses results from experiments performed using a previously-described, simulated environment that was developed for validation of Cognitive Function Synthesis, or CFS, Autonomy. Navigation performance of the Pioneer robot platform used the following metrics: Average Cycle Time per simulation run; Average Wall Contact per cycle; and Average Shock Treatment Activation per simulation run. Two ultrasound, or US, configurations were used while the robot navigated in either the 'preconfigured-reflexes only' mode or the 'Braitenberg Obstacle Avoidance' mode. Results from the "16 sensor" US configuration was generally found to be significantly different from that of the "8 sensor" configuration, independently of obstacle avoidance considerations. Robot performance, when subject to the Braitenberg Obstacle Avoidance algorithm, was also found to be significantly different from 'preconfigured-reflexes only' performance, regardless of US configuration. The difference in Shock Treatment and the Average Wall Contact, observed between the "16 sensor" US setting and the "8 sensor" configuration for the 'Braitenberg Obstacle Avoidance', are likely to be due to the coefficient values adopted for the rear US sensors together with robot position at experiment start. The use of this environment to enable statistical analysis of results, to determine significant difference in obstacle avoidance performance, validates its usefulness as a tool for CFS Autonomy validation.

Keywords: *Cognitive Function Synthesis, Artificial General Intelligence, Associative Memories, Autonomous Navigation, Biomimetic Navigation.*

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1. Introduction

Incorporation of cognitive functionality within Artificial Intelligence, or AI, architectures is a consequence of the perceived failure of AI to adequately resolve the question of intelligence in general, and human intelligence in particular [1, 2]. Cognitive theories guide the implementation of cognitive functions into AI architectures giving rise to Artificial General Intelligence, or AGI. Ragni, Stolzenburg [3] suggest that improved cognitive systems may arise from a deeper understanding of higher-level cognition.

Cognitive theories may result in the incorporation of cognitive functionality as independently subsisting cognitive modules at the symbolic and sub-symbolic levels. Such functionality could include perceptual learning, autonomous action and the fringe robotics properties of Arkin [4]: consciousness, imagination and emotions. Examples of these are the Learning Intelligent Distribution Agent, or LIDA, [2] and MicroPsi [1]. In both cases, cognitive modules such as consciousness or emotions are not treated as an integral part of the system, but as 'add-ons' [5]. Other theories may incorporate Agents into architectures such as Cognitive Robot Control Architecture by Wei, Hindriks [6], which was used on the humanoid Nao robot platform from Aldebaran Robotics. AGI recommends always using a functional structure of complete and integrated cognitive modules in which interdependent relationships between components are identified 'a priori' [1].

Bruckner, Zeilinger, Dietrich [7] observed the existence of an openness to new conceptual frameworks for cognitive approaches to AI amongst researchers. Some examples of this awareness of a conceptual gap are: Emergentist Cognitive Architectures of Biomimetic inspiration [8] that model the brain through the use of ANN-type memory based systems [9, 10]; the Hierarchical Temporal Memory HTM [11] and Darwin VII on NOMAD [12], which emulate brain structure. Thibeault [13] observes that the Neurorobotics examples mentioned effectively couple computational models of neurological biology with robotic agents.

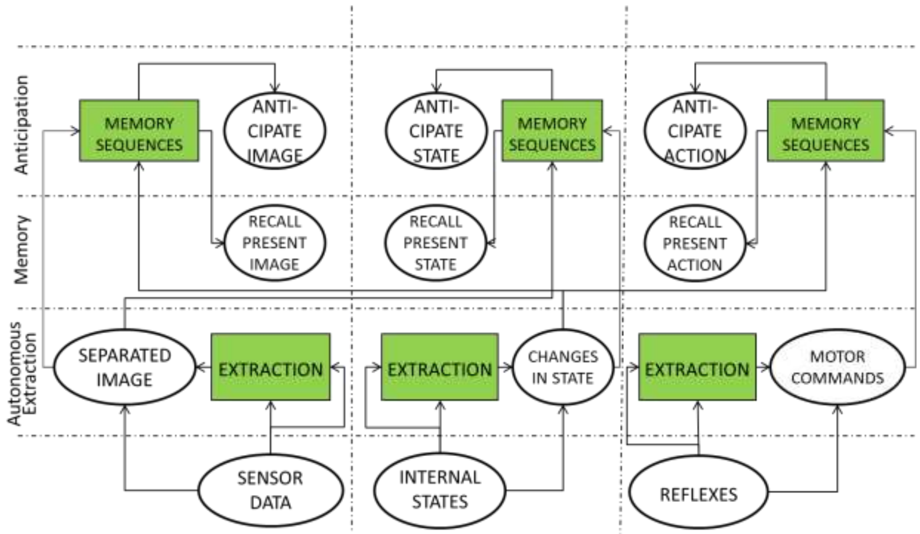


Figure 27: Cognitive Function Synthesis

Pounder, Ellis, Fernandez-Lopez [14] introduced the Cognitive Function Synthesis (CFS) conceptual framework, c.f. Fig. 1, to artificial general intelligence. CFS postulates that at the "core" of intelligence in hybrid architectures, "interdependent" cognitive functions are synthesised through the interaction of various associative memory (AM)-based systems. The authors posit that this synthesis could form an interface layer between deliberative/symbolic and reactive/sub-symbolic layers in hybrid cognitive architectures. Preliminary experiments investigated the plausibility of CFS Autonomous Extraction, Consciousness and Imagination. Initial results suggest that emergent properties, i.e. learned reflexes as suggested by Vernon, Metta, Sandini [15], arise on the basis of pointer-chain sequences and could be useful in robot autonomy. *Interfacing CFS with the reactive/sub-symbolic layer was determined to be a priority to establish plausibility with respect to CFS Autonomy.* CFS needed to be interfaced with a robot platform that would provide input data to it as well as receive output reflex data from CFS framework, for it to be successfully validated for robot navigation autonomy.

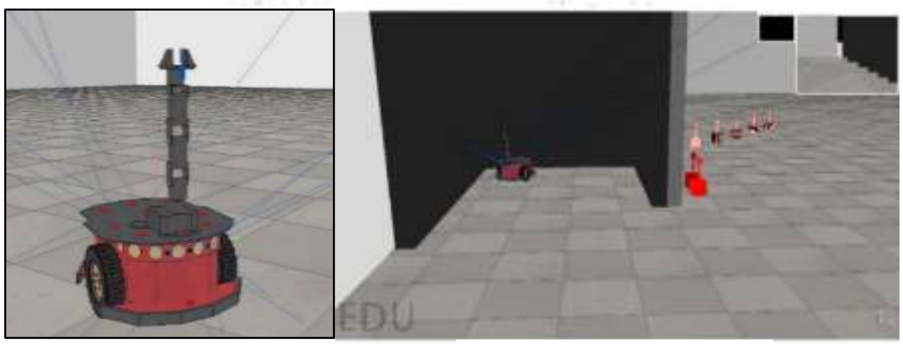
To this end, a previous paper by Fernandez-Lopez, Ellis, Pounder [16] described the simulated environment developed to investigate CFS navigation. However, despite preliminary results suggesting that the simulated environment may be useful as a tool for comparing CFS performance with other Obstacle Avoidance algorithms, these results need to be validated. This paper analyses data to validate the simulated environment and is structured as follows. **Section 2** briefly describes the selected robot platform and presents the state diagram identifying the different stages/behaviours of the Pioneer platform configured as a Behaviour-Based robot. **Section 3** highlights CFS navigation requirements/constraints.

Section 4 compares presented results and discusses robot performance when operating only under reflexes with that when governed by the Braitenberg algorithm. Conclusions are made in **Section 5**.

2. Robot Platforms and Simulated Environments

V-REP was chosen as the simulator for these experiments and was installed on a Lenovo P50 64-bit laptop with an Intel Core i7-6820HQ, and a 2.7 GHz processor with 32GB RAM. Subsequently, code written in C++ with Microsoft Visual Studio 10 was used to run the simulator. The simulator was configured to resemble the environment described in experiments conducted with Darwin VII [17]. The V-Rep supplied 'Eric Rohmer' Pioneer robot model was selected as the robot platform for the simulated environment and was configured with the: wheel joint in force/torque mode; motor enabled; position control disabled.

Figure 2a depicts a V-Rep simulator screenshot illustrating a PhantomX Pincher manipulator mounted onto one such mobile platform. Six vision sensors were also mounted onto the composite platform. Three to the front and two to the back of the mobile platform, while one was affixed onto the manipulator. During these experiments, only the middle-front vision sensor on the platform and the one on the manipulator were used, the latter acting as a proximity sensor. Figure 2b shows the composite robot in the simulated environment.



a) PhantomX Pincher fitted to Pioneer 3DX mobile robot platform with vision sensors.

b) Composite Robot Platform In Simulated Environment.

Figure 28. Screenshots of Simulated Composite Robot Platform

Table 36: Parameters for Detection Value used in Braitenberg algorithm

	Contact/Collision	Obstacle Avoidance
No Detect Limit (No Detection Limit)	0.2	0.5
Max Limit (Maximum Detection Limit)	0.1	0.2

The simulated Pioneer robot was not equipped with bumpers or proximity sensors on which to base a contact-reflex system. Both ultrasound, or US, sensors and vision sensors were configured to use sensory data biomimetically and thus enabled the robot to act in Behaviour-Based fashion. This was achieved for the front vision sensor of the simulated Pioneer, which was configured for a 20 x 15 pixel-sized image, with a Field of Vision of 135°, through a cube-targeting reflex. The US sensors were configured through the use of: the Braitenberg Algorithm, c.f. **Eqs. (1) to (4)**; parameters for 'Contact/Collision' reflex/ behaviour and 'Obstacle Avoidance' behaviour taken from the respective columns of **Table 1**; and the coefficients for either the "8 sensor" or "16 sensor" US configuration, given by **Eqs. (5)** to **(8)**

$$\textbf{Braitenberg (US)}_{\text{Left Motor}} = \sum_{k=0}^{\text{Num Sensors}} \textbf{Left Motor Coefficient}_k \times \textbf{Detection}_k \qquad (1)$$

$$\textbf{Braitenberg (US)}_{\text{Right Motor}} = \sum_{k=0}^{\text{Num Sensors}} \textbf{Right Motor Coefficient}_k \times \textbf{Detection}_k \qquad (2)$$

$$\textbf{Detection}_k = (1 - \textbf{Detection Factor}_k) \qquad (3)$$

$$\textbf{Detection Factor k} = \begin{cases} \dfrac{US_k - \text{Max Limit}}{\text{No Detect Limit} - \text{Max Limit}} & \text{Max Limit} < \text{Sensor Value} < \text{No Detect Limit} \\ 0 & \text{Sensor Value} < \text{Max Limit} \text{ or } \text{Sensor Value} > \text{No Detect Limit} \end{cases} \qquad (4)$$

Left Motor Coefficient (8 Sensors)
= **{-0.2, -0.4, -0.6, -0.8, -1.0, -1.2, -1.4, -1.6, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0}** **(5)**

Right Motor Coefficient (8 Sensors)
= **{-1.6, -1.4, -1.2, -1.0, -0.8, -0.6, -0.4, -0.2, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0}** **(6)**

Left Motor Coefficient (16 Sensors)
= **{-0.2, -0.4, -0.6, -0.8, -1.0, -1.2, -1.4, -1.6, 0.2, 0.4, 0.6, 0.8, 1.0, 1.2, 1.4, 1.6}** **(7)**

Right Motor Coefficient (16 Sensors)
= **{-1.6, -1.4, -1.2, -1.0, -0.8, -0.6, -0.4, -0.2, 1.6, 1.4, 1.2, 1.0, 0.8, 0.6, 0.4, 0.2}** **(8)**

Figure 3 illustrates the state diagram that maps the platform's 'Reactive' behaviour, c.f. [16]. The Braitenberg Algorithm suffers from a tendency to get stuck in local minima. For such occasions, a 'shock' treatment, was introduced to apply instantaneous boosts of high power, in opposing senses, to wheel motors to disengage the robot.

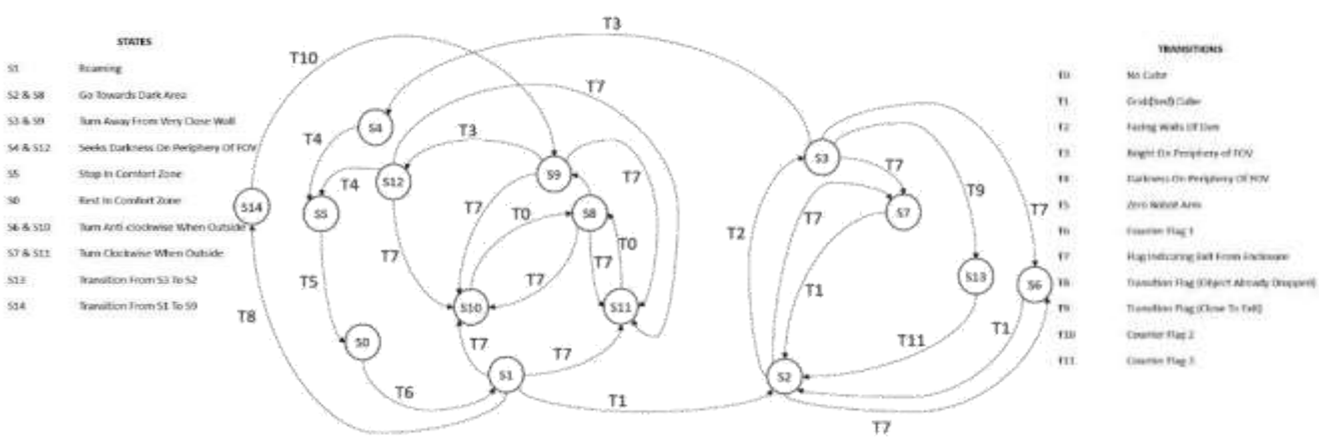


Figure 29: State Diagram Describing Preconfigured Reflexes For BBR

3. Determination of Performance Metrics

Brooks [18] introduced sub-symbolic or reactive robotics as a layered framework in which Obstacle Avoidance was treated as a fundamental behaviour in robot navigation. *As a result of this, obstacle avoidance was chosen as the behaviour for CFS navigation validation.* The V-REP environment was designed with Obstacle Avoidance in mind and CFS navigation was configured as follows. CFS claims an ability to learn to avoid obstacles without specifically being equipped to do so with a preconfigured Obstacle Avoidance behaviour [16]. Therefore, for a given new environment, navigation would initially depend primarily on the 'Contact/Collision' reflex. Subsequent influence by CFS Obstacle Avoidance is expected to manifest itself as the system gains experience. Validation of CFS would, therefore, proceed via a two-pronged approach. CFS performance when governing the simulated robot platform would need to be compared with robot performance when operating under: a) 'Contact/Collision' reflex/ behaviour only, in the absence of any Obstacle Avoidance algorithm; and b) the influence of the Braitenberg Obstacle Avoidance algorithm. Further research would be required to treat with the demands for more sophisticated behaviours and behaviour coordination, as previously highlighted [14].

Metrics for the purpose of validating the environment were established, as follows, to measure Obstacle Avoidance performance, with and without the relevant algorithm,. *The environment would be deemed validated where statistically significant differences in performance can be demonstrated*. A simple measure of effective Obstacle Avoidance can be had by equating lower frequency of wall contact with improved performance[16]. This gives rise to the first performance criteria, c.f. **Eq. (9)**. Additionally, there was the question as to whether the learned avoidance reflex would overcome the tendency of the Braitenberg algorithm to get stuck in local minima when at the centreline of a symmetrical construct such as the corners of the enclosed area. As a result, Shock Treatment Activation, c.f. **Eq. (10)**, was recorded to reflect the number of times the platform got stuck in local minima. Finally, given the improved cycle time that occurred, under pure reflex, with the "16 sensor" US configuration over the one with "8 sensors", cycle time was also measured to determine whether evasive action during learned reflexes might increase the platform's performance under CFS operation, c.f. **Eq. (11)**.

1. Average Wall(/Enclosure) Contact per cycle ($\mathbf{P_{contact}}$):

   The average, per simulation of **j** laps, of the ratios of number of program iterations that robot is in contact with wall per lap, $\mathbf{I_{WCj}}$, to total number of iterations per lap, $\mathbf{I_{Cj}}$.

$$\mathbf{P_{contact}} = \sum_{j=0}^{\text{Total Laps per Run}} \mathbf{(I_{WCj} / I_{Cj}) \,/\, \#\,Laps\ per\ Run} \qquad \mathbf{(9)}$$

2. Average Shock Treatment Activation per simulation run ($\mathbf{ST_{Average}}$):

   The average per simulation of **j** laps, of the number of times during each lap of the den that Shock Treatment, $\mathbf{ST_j}$, was activated.

$$\mathbf{ST_{Average}} = \sum_{j=0}^{\text{Total Laps per Run}} \mathbf{(ST_j) \,/\, \#\,Laps\ per\ Run} \qquad \mathbf{(10)}$$

3. Average Cycle Time per simulation run (**TC$_{Average}$**):

   The average, per simulation of **j** laps, of the times taken for robot to complete each lap of the den, **TC$_j$**.

$$\mathbf{TC_{Average}} = \sum_{j=0}^{\text{Total Laps per Run}} \mathbf{(TCj)/\#\ Laps\ per\ Run} \qquad \mathbf{(11)}$$

4. Results and Discussion

Table 2 summarises the number of simulation runs performed for each combination of system variables considered in these experiments. The initial sample size of 7 was chosen so that using **Eq. (12)** the required number of sample runs to establish 80% confidence that the mean obtained lies with ± 5% of the population's mean could be ascertained.

Table 37: Number of experiments run for each combination of System Variables

System Variables	No Obstacle Avoidance	Braitenberg Obstacle Avoidance
8 sensor configuration	7	7
16 sensor configuration	7	7

$$n = \left[\frac{t_{\alpha/2} \bullet S}{\overline{x} \bullet A/100}\right]^2 \qquad \mathbf{(12)}$$

4.1 Pre-configured Reflexes

Without an Obstacle Avoidance algorithm, autonomous robot navigation is solely dependent on pre-configured 'Contact/Collision' reflexes governed by the Braitenberg algorithm. For all experiments, each iteration of the program/simulator interface was set to 0.5 seconds, the sample time established for CFS operation. The number of iterations completed during the course of a lap varied according to trajectory. A full lap consisted of: a) leaving the back, or recesses, of the enclosure; b) upon exiting enclosure; and c) turning around and returning to back of enclosure.

Two sets of experiments were conducted under these conditions. First, inputs from the eight forward US sensors were used to generate the 'Contact/Collision' reflexes. Figure 4a exhibits the path traced out by the robot, where the line coloured: orange indicates the physical enclosure; grey indicates the limit reached by the robot's centre of area as the chassis "contacts" the physical enclosure; and blue indicates the path followed by the robot's centre of area, or Robot Path. Prolonged contact with the enclosure suggests that the relevant parameter settings made the system's reflex action 'less sensitive' to the surroundings. Second, all sixteen US sensors were likewise used for the 'Contact/Collision' reflexes. This resulted in Fig. 4b and Fig. 4c, which depict the robot path in two distinct experiments. Notice the seemingly reduced contact with enclosure and the 'unpredictable' path followed in some instances.

Results of the 7 separate simulation runs conducted are displayed in **Table 3**. The table displays the mean $\bar{\mathbf{x}}$ and sample standard deviation **S** for these experiments, alongside the calculated sample size, **n**, required to ensure with 80% confidence that the sample means lie within ± 5% of the population's mean, c.f. **Eq. (12)**. Whereas the number of samples were sufficient to be confident about the results for Cycle Time, a considerable number of additional experimental runs would be necessary to garner similar confidence for Average Wall Contact and Shock Treatment for "16 Sensor" US sensor configuration experiments. Therefore, only Cycle Time results can be generalised beyond this experiment.

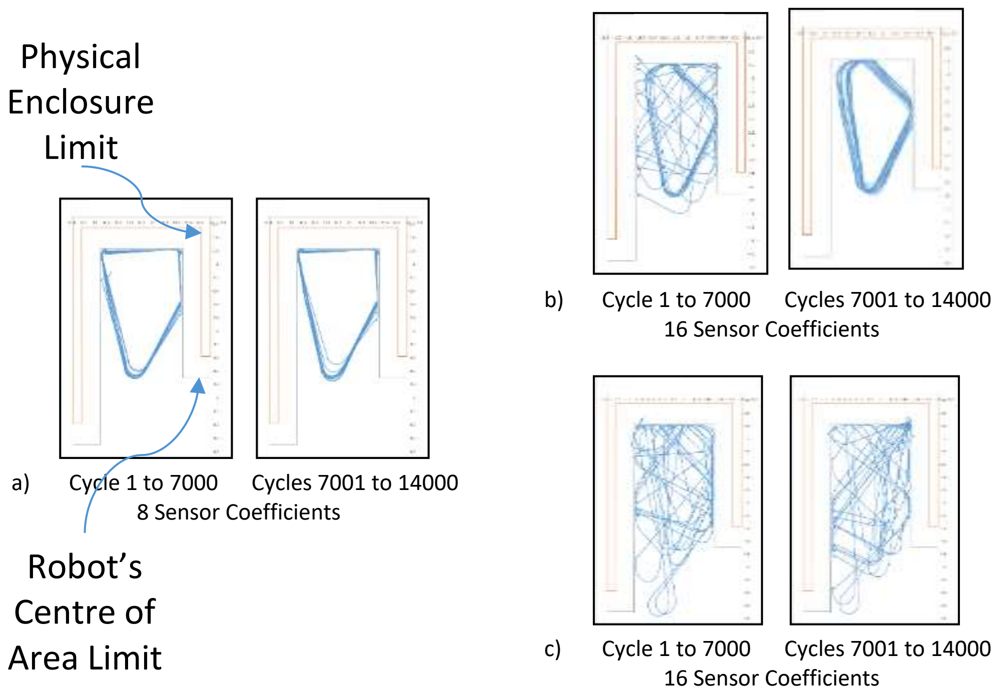


Figure 30: Robot Path Without Obstacle Avoidance: Basic Reflexes Only

Table 38. Results Robot Performance With Only Basic Reflexes

	Average Wall Contact		Average Shock Treatment Activation		Average Cycle Time (mins)	
sample size = 7	8 Sensor	16 Sensor	8 Sensor	16 Sensor	8 Sensor	16 Sensor
No Obstacle Avoidance (NOA) Algorithm	0.1488	0.1506	3.1500	0.1500	4.7302	3.5960
	0.1435	0.1663	3.2750	0.6000	4.7252	3.7857
	0.1487	0.1974	3.1750	0.3750	4.9830	3.8107
	0.1446	0.1980	3.1500	0.5000	4.7246	4.0912
	0.1477	0.2003	3.2250	1.0000	4.9512	4.1098
	0.1495	0.1906	3.1000	0.6000	4.9323	3.9869
	0.1517	0.2041	3.0750	1.0250	4.8489	4.1682
Mean	0.1478	0.1868	3.1643	0.6071	4.8422	3.9355
Sample Standard Deviation	0.0028	0.0203	0.0690	0.3171	0.1154	0.2100
n for 5% Accuracy = (Confidence 1 -α = 0.80) Student t value = 1.440	1	10	1	227	1	3

A marked reduction in the number of "Shock Treatment" episodes with the "16 Sensor" configuration over the "8 Sensor" configuration was observed. It also resulted in a slight reduction in cycle time at the expense of a slight increase in wall contact. This suggests that the former configuration was more effective at reducing instances of local minima than the latter. Results from the double-sided student-t test with α = 0.01, **c.f. Table 4 a)**, showed that these differences were significant. This suggests that, although the additional rear US sensors significantly increased wall contact, it also significantly reduced the use of shock treatment and significantly improved Cycle Time.

Table 39. Independent Samples Hypothesis Test for a Difference Between Sample Means: 8-sensor vs. 16-sensor configuration

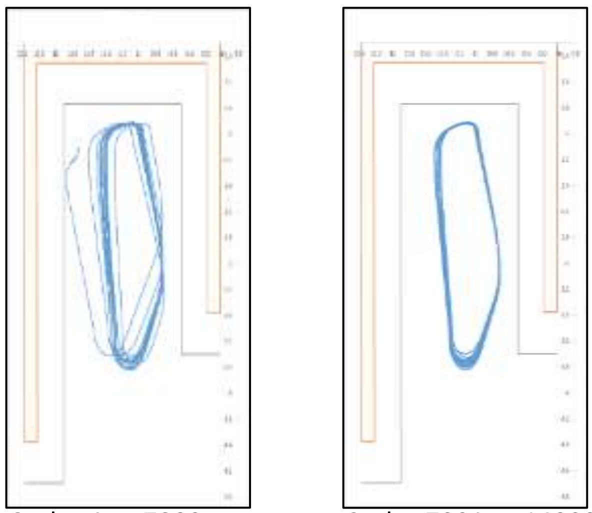
		Average Wall Contact per lap.		Average Shock Treatment Activation per lap.		Average Cycle Time (mins) per lap.	
a)	$H_0 : \mu_8 - \mu_{16} = 0$ $H_1 : \mu_8 - \mu_{16} \neq 0$ α (alpha) =	8 Sensor 16 Sensor Difference	0.1478 0.1868 -0.0390	8 Sensor 16 Sensor Difference	3.1643 0.6071 2.5571	8 Sensor 16 Sensor Difference	4.8422 3.9355 0.9067
	0.01	p-value	0.002109	p-value	0.000000	p-value	0.000003
	No Obstacle Avoidance (NOA) Algorithm	Conclusion :	Reject Null Hypothesis !!!	Conclusion :	Reject Null Hypothesis !!!	Conclusion :	Reject Null Hypothesis !!!
	Student t value = 3.055	In Layman's Terms :	There IS enough evidence to conclude the difference between means is greater than zero !!!	In Layman's Terms :	There IS enough evidence to conclude the difference between means is greater than zero !!!	In Layman's Terms :	There IS enough evidence to conclude the difference between means is greater than zero !!!
b)	$H_0 : \mu_8 - \mu_{16} = 0$ $H_1 : \mu_8 - \mu_{16} \neq 0$ α (alpha) =	Average Wall Contact per lap. 8 Sensor 16 Sensor Difference	 0.0006 0.0015 -0.0009	Average Shock Treatment Activation per lap. 8 Sensor 16 Sensor Difference	 0.0000 0.0929 -0.0929	Average Cycle Time (mins) per lap. 8 Sensor 16 Sensor Difference	 3.8718 3.4631 0.4088
	0.01	p-value	0.018112	p-value	0.000048	p-value	0.000007
	Braitenberg Obstacle Avoidance	Conclusion :	Do not Reject Null Hypothesis !!!	Conclusion :	Reject Null Hypothesis !!!	Conclusion :	Reject Null Hypothesis !!!
	Student t value = 3.055	In Layman's Terms :	There IS NOT enough evidence to conclude the difference between means is greater than zero !!!	In Layman's Terms :	There IS enough evidence to conclude the difference between means is greater than zero !!!	In Layman's Terms :	There IS enough evidence to conclude the difference between means is greater than zero !!!

4.2 Braitenberg Obstacle Avoidance

The Braitenberg Obstacle Avoidance algorithm was superposed over the 'Contact/Collision' reflex behaviour. The number of US sensors used for the 'Contact/Collision' reflexes were also used for Obstacle Avoidance. Figure 5 displays examples of robot paths obtained during these experiments. In the "8 Sensor" configuration, c.f. Fig. 5a, the robot quickly settled to a repeatable path, at a considerable distance from enclosure walls, judging by the space between the robot path, the blue lines, and the grey 'centre of area' line. Apart from this space, the path traced out is similar to that of the robot operating under basic reflexes alone, c.f. Fig. 4b. This continued during the subsequent 7000 cycles. Results were similar for the "16 Sensor" run, c.f. Fig. 5b. Again the robot settled to a fairly repeatable path, at a considerable distance from the enclosure walls.

Table 5 illustrates the data collected over 7 separate runs for each "8 Sensor" and "16 Sensor" experiments. Note that a sample size of 7 was more than sufficient to ensure with 80% confidence that the sample mean for Average Cycle Time was within ± 5% of the population mean. These findings can, therefore, be generalised beyond these experiments. However, it suggests that many more experiments are needed before results of Wall Contact and Shock Treatment can be used with a similar degree of confidence. Differences in mean performance between the platform operating with "8 Sensor" and "16 Sensor", under 'Obstacle Avoidance', was such that although there was an overall reduction in Cycle Time and Shock Treatment, the Average Wall contact increased. Results from the double-sided student-t test with α = 0.01, c.f. Table 4 b), showed that the difference in performance due to the additional sensors was significant for Cycle Time and Shock Treatment, but not for the Average Wall contact.

Given that there were no episodes of Shock Treatment activation in the "8 Sensor" experiments, c.f. Frame A2 in Fig. 6, the sample size could not be calculated giving rise to the '#DIV/0! error' value from the spreadsheet, c.f. Table 5. Figure 6 also highlights the fact that the readings for Wall Contact were all generated within the first lap of the experiment, while readings for Shock Treatment were all generated within the first 5 laps of the experiment. These data points were found to be outliers, falling beyond 3 standard deviations of the sample mean. Nevertheless, they were not removed as they formed part of the comparative data generated during the first 40 laps of the experiment. It is probable that these incidents of Wall Contact may have been the result of the close proximity of the robot to the enclosure at the start of the experiments. Additionally, the instances of Shock Treatment may have resulted from the choice of coefficients for the rear US sensors. Further research would be needed to verify this.



a) Cycles 1 to 7000 Cycles 7001 to 14000

8 Sensor Braitenberg Algorithm

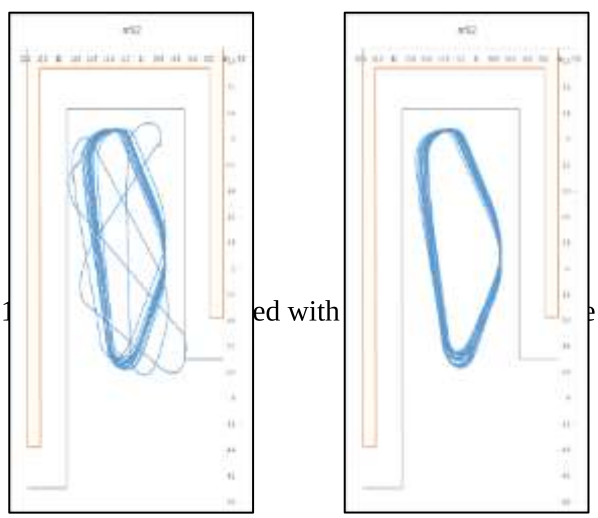


Figure 31 ed with e Avoidance

b) Cycles 1 to 7000 Cycles 7001 to 14000

16 Sensor Braitenberg Algorithm

When the corresponding columns in **Table 3** and **Table 5** are compared, c.f. **Table 6**, the difference in mean performance between the platform operating under reflexes alone and obstacle avoidance, was found to be significant when subjected to the double-sided student t test with $\alpha = 0.01$. *This indicates that the difference in performance was independent of the US configuration and due to the Braitenberg Obstacle Avoidance alone. This validates the environment.*

Table 40: Results Robot Performance With Braitenberg Obstacle Avoidance

	Average Wall Contact		Average Shock Treatment Activation		Average Cycle Time (mins)	
sample size = 7	8 Sensor	16 Sensor	8 Sensor	16 Sensor	8 Sensor	16 Sensor
Braitenberg Obstacle Avoidance	0.0007	0.0022	0.0000	0.1250	3.8255	3.5046
	0.0005	0.0010	0.0000	0.0750	4.0011	3.6102
	0.0008	0.0009	0.0000	0.0750	3.9214	3.3705
	0.0005	0.0026	0.0000	0.1250	3.8031	3.5636
	0.0007	0.0022	0.0000	0.1000	3.7758	3.4895
	0.0006	0.0009	0.0000	0.0750	3.8938	3.2991
	0.0004	0.0009	0.0000	0.0750	3.8822	3.4040
Mean	0.0006	0.0015	0.0000	0.0929	3.8718	3.4631
Sample Standard Deviation	0.0001	0.0008	0.0000	0.0238	0.0773	0.1104
n for 5% Accuracy = (Confidence 1 -α = 0.80) Student t value = 1.440	42	205	#DIV/0!	55	1	1

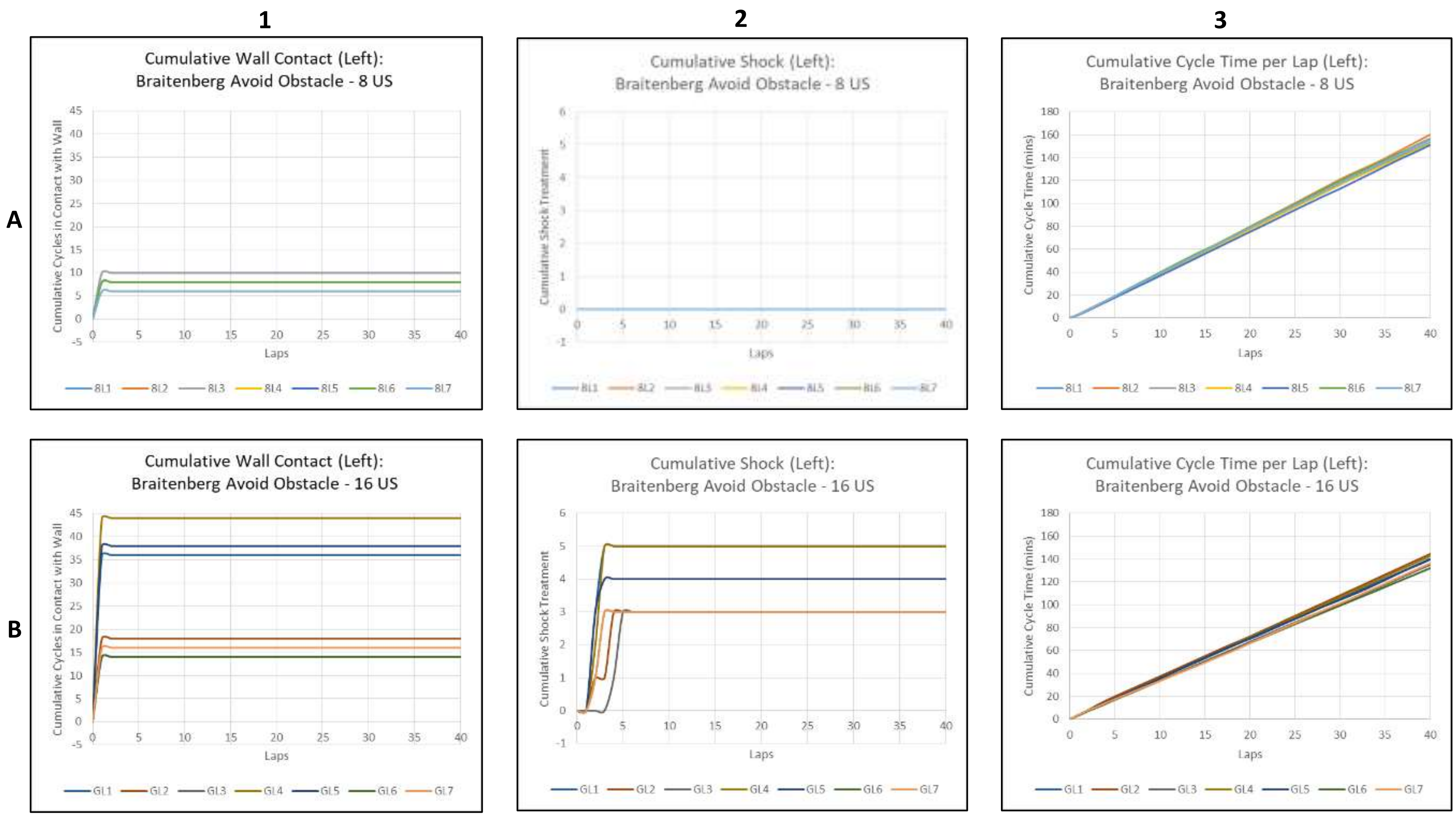


Figure 32: Cumulative Braitenberg Avoidance: 1) Wall Contact, 2) Shock, & 3) Cycle Time For A) "8 Sensor" B) "16 Sensor"

Table 41. Independent Samples Hypothesis Test for a Difference Between Sample Means: Braitenberg vs. No Obstacle Avoidance (NOA)

a)

$H_0 : \mu_8 - \mu_{16} = 0$ $H_1 : \mu_8 - \mu_{16} \neq 0$ α (alpha) =	Average Wall Contact per lap.		Average Shock Treatment Activation per lap.		Average Cycle Time (mins) per lap.	
	8 Sensor	0.1478	8 Sensor	3.1643	8 Sensor	4.8422
	8 Sensor	0.0006	8 Sensor	0.0000	8 Sensor	3.8718
	Difference	0.1472	Difference	3.1643	Difference	0.9703
0.01	p-value	0.000000	p-value	0.000000	p-value	0.000000
NOA (Left) vs Braitenberg (Right)	Conclusion :	Reject Null Hypothesis !!!	Conclusion :	Reject Null Hypothesis !!!	Conclusion :	Reject Null Hypothesis !!!
Student t value = 3.055	In Layman's Terms :	There IS enough evidence to conclude the difference between means is greater than zero !!!	In Layman's Terms :	There IS enough evidence to conclude the difference between means is greater than zero !!!	In Layman's Terms :	There IS enough evidence to conclude the difference between means is greater than zero !!!

b)

$H_0 : \mu_8 - \mu_{16} = 0$ $H_1 : \mu_8 - \mu_{16} \neq 0$ α (alpha) =	Average Wall Contact per lap.		Average Shock Treatment Activation per lap.		Average Cycle Time (mins) per lap.	
	16 Sensor	0.1868	16 Sensor	0.6071	16 Sensor	3.9355
	16 Sensor	0.0015	16 Sensor	0.0929	16 Sensor	3.4631
	Difference	0.1852	Difference	0.5143	Difference	0.4724
0.01	p-value	0.000000	p-value	0.005082	p-value	0.000501
NOA (Left) vs Braitenberg (Right)	Conclusion :	Reject Null Hypothesis !!!	Conclusion :	Reject Null Hypothesis !!!	Conclusion :	Reject Null Hypothesis !!!
Student t value = 3.055	In Layman's Terms :	There IS enough evidence to conclude the difference between means is greater than zero !!!	In Layman's Terms :	There IS enough evidence to conclude the difference between means is greater than zero !!!	In Layman's Terms :	There IS enough evidence to conclude the difference between means is greater than zero !!!

5. Conclusions

A simulated environment, comprised of a Pioneer robot platform in the V-REP simulator developed for validation of CFS Autonomy, was previously described. Equipped with biomimetic reflexes in the Braitenberg sense, it was pre-configured as a Behaviour-Based robot according to its state diagram. Two sets of experiments were conducted. The first experiment allowed the robot to operate in the environment under the influence of the 'Contact/Collision' reflex only. The second experiment studied the robot's performance when the original reflex was subordinated to the Braitenberg 'Obstacle Avoidance' reflex/algorithm. In these experiments, both the "8 Sensor" and the "16 Sensor" ultrasound, or US, configurations were used. Performance was measured by comparing results for Average Cycle Time per simulation run; Average Wall Contact per cycle; and Average Shock Treatment Activation per simulation run.

Results from the first experiment show that the difference in performance of the "16 sensor" US configuration, over the "8 sensor" US configuration, was significant for all metrics. Results from the second experiment, with Braitenberg Obstacle Avoidance, show that the difference in performance of the "16 sensor" over the "8 sensor" US configuration, was significant for the Average Cycle Time and Average Shock Treatment Activation, but not for Average Wall Contact with Obstacle Avoidance. In both cases, there was an increase in Average Wall Contact with the "16 sensor" US configuration, over the "8 sensor" US configuration. This increase, however, was 'not significant' in the case of obstacle avoidance, and may be due to the robot's close proximity to the enclosure at the experiment's start. The choice of coefficients for the rear US sensors may be responsible for both: the significant increase in Average Wall Contact in experiments without Obstacle Avoidance; as well as the changes observed in Shock Treatment. *Results also show that, where US sensor configuration is held constant, the difference in performance of the Braitenberg algorithm was significant on all metrics.* Further investigation into the effect of varying robot position as well as US coefficient values is needed before these results could be generalized beyond these experiments.

These results validate the use of the simulated environment as a tool to statistically compare the performance, between the simulated robot acting with and without an obstacle avoidance algorithm. As such, it can be used as a tool to measure and compare the relative performance in CFS navigation autonomy experiments.

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