Robots with Purpose

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Abstract

In this article I apply Perceptual Control Theory to Braitenberg Vehicles. Computational models can only explain systems in functional terms, as a transformation from input to output. Living, and indeed robotic systems are so much more, having to engage with and survive within a world. Robots, of course, are very simple machines but purposeful explanations of robotic behaviour can a powerful alternative to the computational view.

1 INTRODUCTION

This article was written in response to an observation in Richard Marken's 'Doing Research on Purpose' [4, p.17], about the presentation of Braitenberg vehicles as stimulus-response (S-R) models. What if we do the opposite, and apply the methods of experimental psychology, specifically Perceptual Control Theory (PCT), to gain a fresh understanding of these vehicles' behaviours? Might we think about them as robots with purpose?

Valentino Braitenberg's, 'Vehicles: Experiments in Synthetic Psychology' [1] inspired many to explore its strange intersection of cybernetics and artistry. From the outset it describes creatures that are openly mechanistic – a simple brain laid bare for all to see – but then labels them with suggestively *purposeful* names starting with 'getting around', leading rapidly onto 'Fear and Aggression', and then 'Love'. I think it is no accident that the book challenges us with these different interpretations, inviting us to consider mechanism versus purpose. In this article I focus on the first two vehicle designs, Vehicles 1 and 2 (specifically 2B, or 'Aggression'), analysing them in terms of their purposeful, goal-seeking behaviour.

Braitenberg vehicles have sensors and motor output. There is a simple causal arc from sensor to motor output, so vehicles *can* be understood as simple stimulus-response systems. Lacking any internal state (at least up to Vehicle 4) any given input produces a determined output. When placed in an environment with a light source they react and move. This movement, in turn, causes a change in the light stimulus. These two causal pathways, from the sensors to the motors within the vehicle, and then the motors affecting the environmental stimulus, form a self-referential closed loop. We could describe the behaviours of the vehicle and its environment as a set of simultaneous equations, meaning that they act upon each other simultaneously and continuously. Where this mutual embrace acts to stabilise itself and maintain equilibrium we describe this virtuous cycle as negative feedback. For the experiments below, our vehicles are evaluated within a computer simulation of the vehicle and a simple environment with a single source of light.

2 PERCEPTUAL CONTROL THEORY

The aim of this article is to apply the methods of experimental psychology to Braitenberg's vehicles, looking for negative feedback control manifesting as purposive behaviour. We test that this goal-seeking negative feedback loop is real and not just a linguistic turn. To do that we must define a hypothesis about the variable controlled by the loop. William Powers' Perceptual Control Theory (PCT) [6] asserts that organisms are not in the business of controlling their behaviour, but of their *perceptions*. This reflects earlier observations by Merleau-Ponty [5, p. 37],"the motor devices appear as the means of re-establishing an equilibrium, the conditions of which are given in the sensory sector of the nervous system." Our hypotheses about vehicle behaviour must accordingly describe not the motor outputs, but variables that it is possible for a vehicle to perceive, or a simple function of these directly available sensory inputs. For example, a vehicle with a *single* light sensor cannot in principle control distance because the luminosity of the light source is unknown to it, and it cannot compute distance from the perceived brightness alone. the Our first thought might be that the vehicle is phototactic and seeks to maintain a constant level of illumination.

A system can be said to control a variable if every disturbance tending to cause a deviation from the goal state results in a behaviour that acts in opposition to the disturbance [6]. PCT provides the tools for testing whether any of these hypothesised variables is actually controlled by the vehicle. Powers' Test for the Controlled Variable (TCV) [4] is an objective way to determine which, if any of these hypotheses is true. Control Theory tells us how we can keep a controlled variable in, or near, a reference state. The idea is that if we disturb the system by manipulating another variable then the hypothesised controlled variable will hold constant if it is truly under control, or else it will vary with the disturbance. If we have multiple hypotheses then we should try to find a disturbance that will affect one but not the other.

In our experiments we will test our hypotheses by introducing a disturbance in the brightness of the light source. A reference value for each hypothesised variable is estblished with the light source at full illumination. We then collect a number of readings for each variable at different levels of luminance, and calculate the residual difference between the observation and the respective reference values for each hypothesis. The residuals $\hat{y}_i - y_i$ measure the difference between the reference value, $\hat{y}_i$ (in this case held constant over i), and the observed values, y_i. The results are summarised in the calculation of the root-mean-square deviation (RMSD) of these residuals for each hypothesis, as in equation 1 below, where n is the number of observations.

$$\text{RMSD} = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{n}} \tag{1}$$

The root-mean-square deviation is sufficient to be able to make a determination about each hypothesis in isolation but to compare different hypotheses we need to normalise the results to account for observations on different scales. The *normalized root-mean-square deviation* (NRMSD) may be calculated by dividing the RMSD by the mean, $\bar{y}$, of the observations as in equation 2, below. This is expressed as a percentage with lower values indicating less residual variance.

$$\text{NRMSD} = \frac{\text{RMSD}}{\bar{y}} \tag{2}$$

3 VEHICLE 1

Braitenberg's vehicles are wonderfully under-specified. We know the eyes must be directional, but they might just as easily measure a chemical or temperature gradient, as measure light. For argument's sake, we will think of this as a light sensor that produces an analogue signal in proportion to the amount of light falling upon it. By 'motor outputs', Braitenberg means anything that can provide a motive force, not just electric motors. They could easily represent the flagella on a bacterium.

A simple light-sensing 'eye' can provide directional information by virtue of Lambert's cosine law which states that the illuminance on a surface varies with the cosine of the angle of incidence. With a light source directly ahead at $0°$, it receives full illumination ($cosine(0) = 1$), falling to zero at a $90°$ angle of incidence ($cosine(\pi/2) = 0$). However, if this were a regular photocell and the light moves behind it then it would receive no input at all and the signal remains at 0. With this arrangement, vehicles would quickly get into the *doldrums* where they don't receive enough light to move, making for a very boring and unconvincing demonstration. Things get a lot more interesting if we give them wrap-around vision such that light from behind provides a negative stimulus ($cosine(\pi) = -1$). Given that nature's nerve bundles cannot carry a negative signal we may add an offset of 1 to provide a signal in the range 0 to 2, inclusive. This kind of sensor is also straightforward to construct in a physical robot by arranging pairs of photocells back to back.

As can be seen in Figure 1, Braitenberg Vehicle 1 has just one eye and one motor. Vehicle 1 cannot obtain any information about the direction of the light source with respect to its sagittal axis, running from the front to back of its body. We might think of its behaviour as a form of *klinotaxis* which occurs in organisms with sensors that are not paired. Only by moving through, and sampling its environment can it move relative to a sensory gradient.

The sensory signal is conveyed from the eye to the motor by the wire or nerve fibre connecting them, causing the motor to vary continuously in its output in proportion to the input. The brighter the light, the faster it drives the motor. This vehicle might

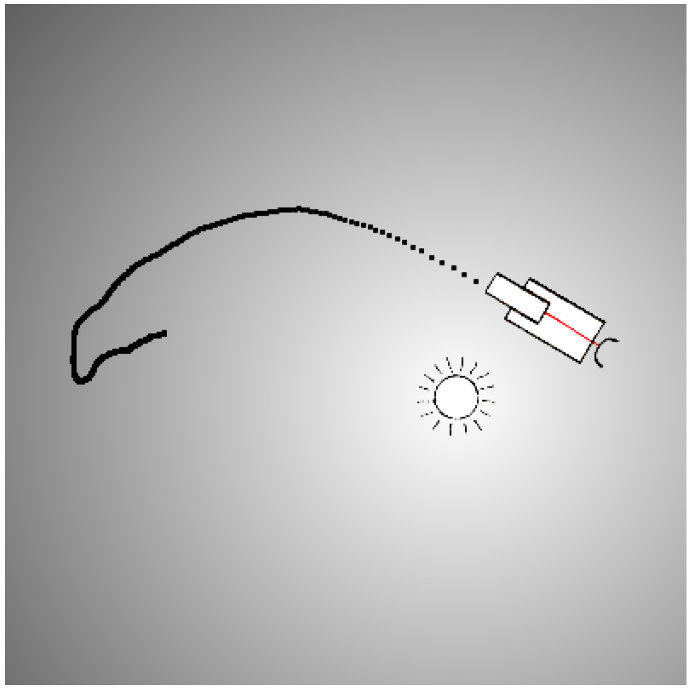

Figure 1: Braitenberg Vehicle 1 is stimulated by light, making it move faster as it approaches the light source.

seem trivial, but nature employs something very close to this design in the humble E. coli bacterium. Not just a source of food poisoning, but one of natures own vehicles. Vehicle 1 exploits a feature of the world faced by simple motiles, and even exploited by E. coli; as the vehicle presses forward through its medium, it encounters pushback from frictional forces that introduce randomness. To quote Braitenberg [1, p. 5], “Once you let friction come into the picture, other amazing things might happen. As the vehicle pushes forward against frictional forces, it will deviate from its course. In the long run it will be seen to move in a complicated trajectory, curving one way or the other without apparent good reason. If it is very small, its motion will be quite erratic, similar to ‘Brownian motion’, only with a certain drive added.”

What can we say about this ‘complicated trajectory?’ It’s clear that the vehicle speeds up as it heads towards the light, but it also tends to overshoot so that it spends little time in the immediate vicinity of the light. At the other extreme, as the vehicle moves out into the darkness it lacks the impetus to move out any further. Only when it randomly turns to face the distance light does it find sufficient energy to return, slowly at first, to the warmth of its sun. The behaviour of Vehicle 1 must be understood probabilistically, with these two opposing effects shaping the probability distribution of the vehicle’s position. Might there be a ‘Goldilocks’ zone’ favourable to Vehicle 1 lying somewhere between these two extremes?

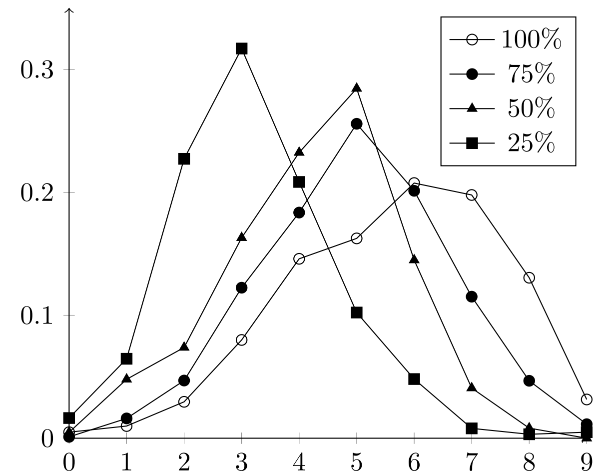

Figure 2: Density trace (histogram) with the horizontal axis showing distance from the light source partitioned into 10 bins running from minimum to maximum distance (The centres of the bins run from 0.5 to 9.5). Each bin is adjusted for its area and normalised. Each trace illustrates increasing disturbance, from 100% (no disturbance) down to 25% of light source luminosity.

To simulate the random buffeting of friction a small random angle is added to the vehicle heading on each cycle of the simulation. Its heading is a random-walk through the angles of orientation and therefore this variable is completely beyond the control of the vehicle. Our first hypothesis (H1) will be that, despite its semi-random walk, Vehicle 1 seeks a specific level of brightness. For comparison, hypothesis 2 (H2) is that Vehicle 1 controls for distance. Hypothesis 2 is really only a pseudo-hypothesis, as we reasoned earlier that Vehicle 1 cannot perceive distance. It may use apparent brightness as a proxy for distance, but this weakens the connection between the two, and hence its ability to control for distance. We therefore expect its control over illumination to be stronger than that for distance.

If Vehicle 1 can be thought of as a control system at all, the effect will be very weak and the disturbance may be only weakly opposed [6, p.234]. We must run a very long trial to see any effect. Each test run of Vehicle 1 lasts for 100K cycles in which its position is recorded in one of 10 bins, representing equispaced concentric rings, or annuli, centred on the light source, and going outwards to the edge of the simulated space. As these 10 concentric annuli have equally spaced radii, the bins do not have equal area. To adjust for these different bin sizes, these values are divided by the bin size. What is shown in the density trace of Figure 2 are the probability densities of each bin after adjustment, normalised such that they sum to 1. A vehicle moving about its environment with diffuse omni-directional lighting would result in all 10 bins having approximately equal probability densities around 0.1.

The disturbance that will be introduced is to vary the luminosity of the light source. An initial run without any disturbance is used to determine initial reference, or hypoth-

	H1 (brightness)	H2 (distance)
reference	0.1698	0.6068
luminosity		
100%	0.1646	0.6162
75%	0.1562	0.5479
50%	0.1382	0.4756
25%	0.1124	0.3729
mean	0.1428	0.5031
RMSD	0.0336	0.1376
NRMSD %	0.2349	0.2730

Table 1: Analysis of Vehicle 1 brightness and distance data with increasing disturbance (decreasing luminosity). The four distance data points are the mean of each trace from Figure 2, while the brightness is computed from this and the luminosity. The RMSD summarises the squared residual difference of each data point from the reference. For comparison of H1 and H2, these are normalised (NRMSD) using the mean of the data. We see a small difference in control for brightness (H1) over that of distance (H2). However, we must reject H2 because Vehicle 1 cannot perceive distance.

esised goal, values for the vehicle's average distance from the light source, and the apparent brightness at this position. These values are obtained from the normalised histogram by forming a weighted mean of the histogram data, with weights representing the mid-point of each annulus. Distance is adjusted to lie within the interval, 0 to 1, so in the case of the a vehicle moving around receiving only diffuse omni-directional lighting the weighted mean distance will be around 0.5. Four further runs of 100K cycles are used to produce the density traces in Figure 2, first with 100% luminosity (no disturbance), then introducing disturbances of 75%, 50%, and 25% luminosity. The apparent brightness is a function of the luminosity of the light source (known to the observer) and the distance, in accordance with the inverse square law.

It can be seen in Table 1 that the existence of the 'Goldilocks' zone' is borne out by the data. The data without disturbance (trace 100%) shows a clear peak, with a weighted mean of 0.6162. When the light source weakens, we see that the vehicle moves in closer to compensate. A visual inspection of the density traces shows that the peaks move to the left with increasing disturbance, showing that the vehicle is more likely to be closer to the light source as it grows dimmer.

4 VEHICLE 2

Braitenberg vehicle 2 has two eyes, which allow it to determine the direction of the stimulus and move accordingly (tropotaxis). Its response to light may be described as 'has a fight or flight', and Vehicle 2B specifically demonstrates the latter, accelerating towards the light in a way that might be considered aggressive. It has two eyes and

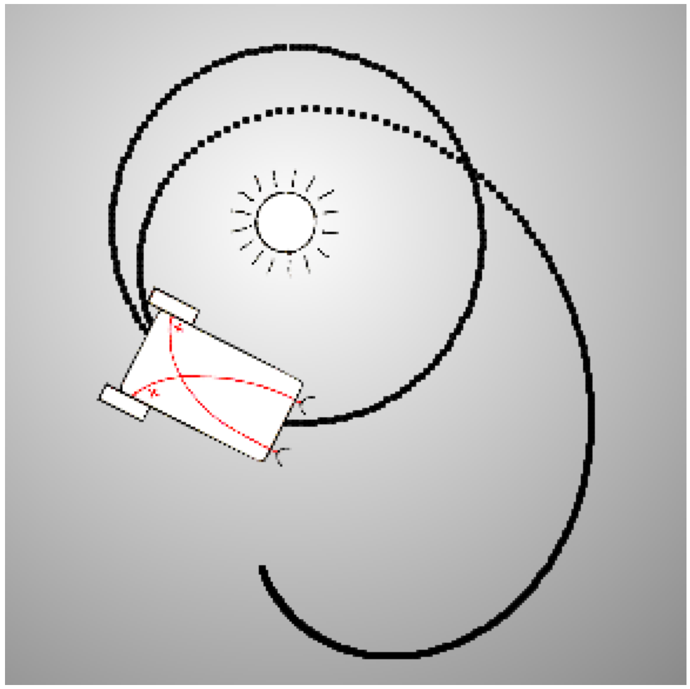

Figure 3: Braitenberg Vehicle 2B approaches the light source ‘aggressively’ then settles into a close orbit.

two motors, such that the motors are driven differentially according to the difference in light level received by the two eyes. This results in positive phototaxis, or directed movement towards a light. As the vehicle gets closer to the light the stimulation increases, causing it to go faster and faster, until it runs into the light source (hence the name, ‘Aggression’).

The ‘brain’ of Vehicle 2B is shown graphically in Figure 3 which shows that each sensor is connected via an excitatory connection to one motor, indicated by the ’+’ at the end of the nerve fibre. In its simple nervous system, the signals from each eye crosses-over to stimulate the motor on the opposite side of its body. Thus light stimulation on one side causes the motor on the opposite side to run faster, acting to steer the vehicle towards the light. These crossed connections are common in vertebrates, including humans. The Spanish neuroanatomist Ramón y Cajal was the first scientist to map the detailed neural structure of the brain in 1899. He observed optic nerve fibres from the half of the eye closest to the nose cross over to the opposite side of the brain. However, where each human optic nerve carries a million or so separate nerve fibres, the humble Vehicle 2 has just two.

These *tropisms* are seen in nature, not only as movements towards or away from a light source but also as changes in orientation with respect to light. The sea-anenome *Actinea cereus* extends its tentacles perpendicularly with respect to a weak light source but in parallel with more intense light, regulating the amount of falling on it [7]. Similarly, the dorsal light reaction in moths allows them to keep the moon above them, one reason why they become entrapped by street lamps [3].

The arrangement of the sensors and the crossover network mean that the vehicle is in equilibrium when a light source is directly ahead, and the stimulation of both motors is equal. This is what *causes* the vehicle to ram the light source head-on. Can this be said to be a goal of the vehicle? This 'aggressive' event is a little short-lived to study at length, so I look to subsequent behaviour after it has run into the light. If we allow it to pass through unharmed then a small imbalance one way or the other will again cause it to turn towards the light. In the designs explored here there comes a critical point where the turning circle of the vehicle holds it within a close *orbit* around the light source. Again the vehicle has entered some kind of equilibrium, orbiting clockwise or anti-clockwise around its source of energy.

The eyes are mounted on the vehicle body with a disparity of $90°$ from each other, each one facing outwards from the centre-line of the vehicle at an angle of $45°$, or $\pi/4$ radians. If θ is the angle of the vehicle to the light source (how much it would have to turn to face the light), then the light received by the right eye varies with the *cosine* of θ with this offset. The $90°$ angle between the eyes introduces a phase-shift such that the light received by the left eye varies with the *sine* of θ. The identity of Equation 3 implies that after factoring out the illumination, the difference between the left and right eyes is proportional to $sin(\theta)$, in other words it is a straightforward representation of the angular deviation from the light source. Note that this holds whether or not we add a constant to each side to bring them into the positive range, as with Vehicle 1, because these simply cancel each other out.

$$\begin{aligned} sin(x) \pm cos(x) &= \sqrt{2}\, sin(x \pm \pi/4) \\ l &= sin(\theta + \pi/4) + 1 \\ r &= cos(\theta + \pi/4) + 1 \\ l - r &= \sqrt{2} * sin(\theta) \end{aligned} \tag{3}$$

If we look at the kinematics of Vehicle 2B, The angular velocity of the vehicle, ω, defined in Equation 4, is proportional to the difference between the two eyes. The variable, d, is the distance between each wheel d the centre-line of the vehicle, so $2d$ is the distance between the two wheels; the further apart they are, the slower the vehicle turns. The angular velocity is influenced by the brightness of the light, b. For a light source dead-ahead or dead-astern the stimulation of both sensors is identical and they cancel out, or equivalently, $sin(0) = sin(\pi) = 0$, utilising Equation 3 above. The difference, and hence the angular velocity, is zero.

$$\omega = b\,(l - r)/2d \tag{4}$$

The linear velocity, v, of the vehicle is simply the average of the two motors. Imagine both motors running forwards at full speed; the average will be the same. Now imagine one motor running forwards at full speed and the other running backwards at the same speed; they average out at 0 as the vehicle simply spins around on the spot. This is modulated by the brightness, b, so that it turns faster in brighter light.

$$v = b\,(l + r)/2 \tag{5}$$

The turning radius, r, of the vehicle is given by $v = r\omega$. Solving for r in Equation 6 , we see that the brightness terms cancel out. There are two additional interesting orientations to the port and starboard of the vehicle. With the light source $\pm 90°$ to the axis, $sin(\theta) = \pm 1$ and so the difference between the eyes simplifies to $\pm\sqrt{2}$. At the same time, the sine and cosine response of the eyes cancel each other out exactly, leaving us only with the added constants which average out to a linear velocity of 1 as the numerator. The implication of this is that once the vehicle has achieved a stable orbit, the turning radius is a function only of the distance between the two wheels, and so the vehicle will follow a stable clockwise or anti-clockwise orbit independent of brightness.

$$\begin{aligned} r &= v/\omega \\ &= \frac{b\,(l+r)/2}{b\,(l-r)/2d} \\ &= 2d\,\frac{(l+r)/2}{(l-r)} \\ &= 2d\,\frac{(l+r)/2}{\sqrt{2}\,sin(\theta)} \\ &= \frac{2d}{\sqrt{2}} \text{ where } \theta = 90° \end{aligned} \tag{6}$$

Powers states [6, p.233], "A controlled quantity is controlled only because it is detected by a control system." Given that a system may only control that which it can perceive, then it cannot be said to control its turning radius; this is merely a contingent fact that follows from the hypothetical control of θ. We might expect a phototactic vehicle to adapt by moving closer to the light source to keep the illumination constant, whereas a vehicle that is concerned with the angle to the light source would not be so affected. Our first hypothesis (H1) then is that, like Vehicle 1, Vehicle 2B seeks to maintain a constant level of brightness through phototaxis. Alternatively, we might assume that, like the moth, the vehicles' dorsal light reaction holds the angle, θ, to the light source constant; this is hypothesis 2 (H2).

In any experiment based on PCT, the experimental subject is not simply responding to the error, but to the difference between what they perceive (illumination or angle) and a *reference*, or goal condition. We may establish these reference conditions by observing the system *without* disturbance. Following an initial run in which we record the reference values with no disturbance, we run ten test trials each with increasing levels of disturbance from 100% and 10% of full luminosity. Each test run lasts for 10K cycles which gives the vehicle sufficient time to settle into a stable orbit. At the end of each run, we record the apparent brightness at the position of the vehicle, and its angle to the light source (with 0° representing dead-ahead).

The results are summarised in Table 2. With increasing disturbance the vehicle slows down as there is less sensor stimulation. As speculated above, the vehicle enters

	H1 (brightness)	H2 (angle)
reference	1.8173	1.6407
luminosity		
100%	1.8173	1.6407
90%	1.6195	1.6331
80%	1.4255	1.6257
70%	1.2352	1.6184
60%	1.0486	1.6112
50%	0.8656	1.6042
40%	0.6860	1.5972
30%	0.5097	1.5905
20%	0.3367	1.5838
10%	0.1668	1.5772
mean	0.9711	1.6082
RMSD	0.9967	0.0383
NRMSD %	1.0264	0.0238

Table 2: Analysis of Vehicle 2 brightness and angle data with increasing disturbance (decreasing luminosity). Observations for brightness and angle are taken for each of the ten levels of disturbance. The RMSD summarises the squared residual difference of each data point from the reference. For comparison of H1 and H2, these are normalised (NRMSD) using the mean of the data. We see two orders of magnitude improvement in control for angle (H2) over that of brightness (H1).

a stable orbit and as the RMSD for H1 (brightness) shows, there is very little movement towards the light source commensurate with the disturbance, leading to increased differences in brightness. The RMSD for H2 (angle) is very low, indicating that the vehicle is able to control for angle, and as a consequence, the orbit has a near constant turning radius. Looking at the normalised results, the NRMSD for H2 (angle) is 2 orders of magnitude less than that of H1 (brightness), so we consider this to be additional evidence that the angle to the light source *is indeed* the controlled variable. We conclude that the controlled variable is the angle of the vehicle to the light source, independent of the luminosity of the light source over a wide range of values.

Despite the large disturbance, the vehicle behaves as if it is comparing the perceived state of affairs with a reference perception of how the world *should* look. Yet this behaviour is not explicitly coded into the vehicle simulation, but emerges as a consequence of the interactions between its parts [2], including the type and arrangement of the sensors, the robot kinematics, and the virtual world itself.

5 CONCLUSION

A computational model of a system describes the algorithmic transformation of input data to output data, which can be understood as a Stimulus-Response (S-R) system. Where computers may be understood as disembodied information-processing machines with no loss of explanatory power, it is precisely the *embodiment* of robotics that is key to our understanding of them. Even where a faithful simulation can be built entirely within the computer, as with Braitenberg's vehicles, the simulation still lacks an account of *purpose*. Control theory, in particular the Test for the Controlled Variable (TCV), provides us with the tools for evaluating objective hypotheses about the purposes of an embodied robot from its observed behaviour.

The surprising thing about Vehicle 1 is that it is goal-directed at all. Yet observations of its biased random walk reveal its long term *klinotaxis* where it exhibits a favoured level of brightness. The big surprise of Vehicle 2 is that while it is able to hold a circular orbit at a constant distance from the light source in the face of extreme disturbance in luminosity, this is not the controlled variable because it cannot be perceived by the robot. This is merely a contingent fact that follows from the vehicles' ability to control its angle to the light source.

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