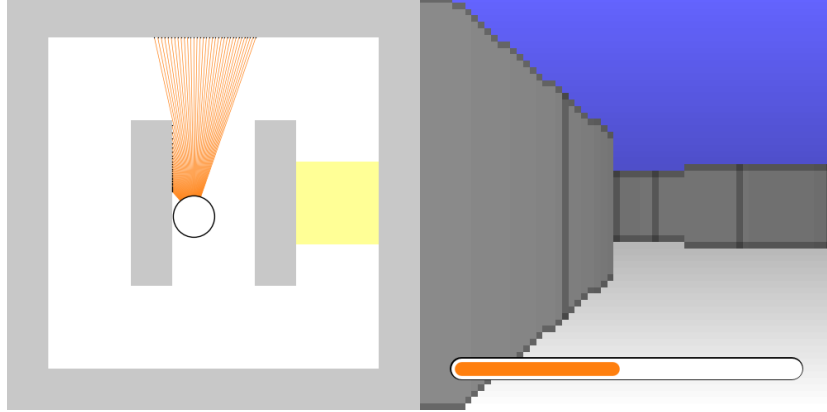


# 1 Programmatoid braincraft challenge solution

Let us consider the following digital experimental setup, as described in braincraft challenge presentation<sup>1</sup>.

## 1.1 Simplified problem statement



The braincraft challenge<sup>2</sup> bot moves at a constant with sensor inputs and one orientation output, it uses some energy and refill this energy on a given yellow location. The 2D space size is  $[0, 1] \times [0, 1]$ . The bot starts in the middle and oriented at 90, i.e., upward.

Input variables	
$p_l \in [0_{\text{wall-hit}}, 1_{\text{no-wall}}[$	Leftward proximity, max value of the $[0, +30^\circ]$ range 32 left sensors.
$p_r \in [0_{\text{wall-hit}}, 1_{\text{no-wall}}[$	Rightward proximity, max value of the $[-30^\circ, 0]$ range 32 right sensors.
$c_{l\bullet} \in \{0, 1\}, \bullet \in \{b_{\text{blue}}, r_{\text{red}}\}$	Leftward binary red and blue color detectors.
$c_{r\bullet} \in \{0, 1\}, \bullet \in \{b_{\text{blue}}, r_{\text{red}}\}$	Rightward binary red and blue color detectors.
$g_e \in [0_{\text{death}}, 1_{\text{full}}]$	Energy gauge value.
Output variable	
$d_o \in [-5, 5]$	Orientation difference, saturated at $\pm 5^\circ$ .

With respect to the original braincraft challenge:

- we consider two leftward and rightward “average” sensors only,
- color is input as binary variables, and always available,
- the wall hit indicator is not used.

<sup>1</sup><https://github.com/rougier/braincraft/blob/master/README.md#introduction>

<sup>2</sup><https://github.com/rougier/braincraft>

## 1.2 A putative controller

### 1.2.1 Input preprocessing

#### Proximity sensors

**Motivation** Simplifies the left-right navigation by compacting the leftward and rightward sensors as a simple pair of input.

**Implementation** A simple sum or average could be used, thus using directly a linear combination of the input in afferent units.

Then, if appropriate, the maximal and the average operators can be combined, e.g.<sup>3</sup>:

$$\begin{aligned} p_{\dagger} &\leftarrow \log \left( \sum_{k \in K} \exp(\mu p[k]) \right) / \mu \\ &= \frac{1}{K} \sum_k p_k + \log(K) / \mu + O(\mu) \\ &= \max_k(p[k]) + o\left(\frac{1}{\mu}\right) \end{aligned}$$

where  $K$  stands for the left or right sensor related indexes,  $p[k]$  stands for the sensor proximity value, and  $\mu > 0$  parameterizes the balance between the max (for large  $\mu$ ) and the average (for small  $\mu$ ) operators, as shown in Fig. 1.

#### Color sensors

**Motivations** Again, color blob detection is to perform either on the left or on the right, allowing the color input to be compacted. For each color, a channel is specified, simplifying the programmatoid implementation and providing an input closer to biological colored vision. Since the setup color input is a discrete color index, the channel value is binary, accounting for the presence, or not, of a least one related color index.

**Implementation** For the distributed implementation, each camera color index value is mapped on each color channel input with the 0 value if the color is different and the 1 value if equal, e.g., using step unit:

$$\begin{aligned} c_{\dagger \bullet} &\leftarrow H(\sum_{k \in K} (1 - D(i_{\bullet} - c[k]))), \\ &\quad \dagger \in \{l_{\text{left}}, r_{\text{right}}\}, \bullet \in \{b_{\text{blue}}, r_{\text{red}}\} \\ D(x) &\stackrel{\text{def}}{=} H(x - \epsilon) + H(-x - \epsilon) = \text{if } |x| < \epsilon \text{ then } 0 \text{ else } 1, \epsilon \ll 1 \end{aligned}$$

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<sup>3</sup>Let us derive the formula:

- The series at  $\mu \rightarrow 0^+$  is easily obtained from any symbolic calculator writing, e.g.:  
`series(log(sum(exp(mu * p[k]), k = 1..K)) / mu, mu = 0, 2);`

- There is no obvious series development at  $\mu \rightarrow +\infty$  but, considering  $p[1] \leq p[2] \leq \dots \leq p[K]$ , without loss of generality, i.e., that -for the notation- index's order correspond to decreasing values, we obtain from straightforward algebra:

$$\begin{aligned} &\log \left( \sum_{k \in \{1 \dots K\}} \exp(\mu p[k]) \right) / \mu = p[1] + \rho / \mu \\ \rho &\stackrel{\text{def}}{=} \log \left( 1 + \sum_{k \in \{2 \dots K\}} \exp(-\mu (p[1] - p[k])) \right) \\ &\text{with } 0 \leq \rho \leq \log(1 + (K - 1) \exp(-\mu (p[1] - p[2]))) \leq \log(K) \end{aligned}$$

so that  $\lim_{\mu \rightarrow +\infty} \rho = 0$  and  $\rho = o(\mu)$ , yielding the expected result.

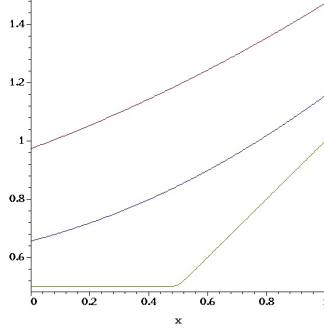


Figure 1: Representation of the exp-log function for  $K = 2$ ,  $p[2] = 1/2$ , with  $p[1] \in [0, 1]$  and  $\mu \in \{1, 2, 100\}$ . With small  $\mu$  it is closed to linear average, whereas for  $\mu = 100$  it is close to  $\max(x, 1/2)$ .

where  $K$  stands for the left or right sensor related indexes,  $i_{\bullet}$  stands for the color index, and  $c[k]$  stands for the sensor color index value.

### Energy measurement

**Motivation** The energy increase accumulation has to be pre-processed, since used in some task.

### Processed Variables

$g_{cb} \in [0, 1], b \in \{1, 2\}$   $g_{cb}|_{t=0} = 0$  Last and last-before-last cumulative energy increases.  
 $g_{eb} \in [0, 1], b \in \{1, 2\}$   $g_{eb}|_{t=0} = 0$  Last and last-before-last energy value.

Here instantaneous energy increase is  $(g_e - g_{e1})$ ,

### Implementation

Cumulating energy increase starts, saving last increase in  $g_{c2}$ .

if  $\underbrace{g_e > g_{e1} \text{ and } g_{e1} < g_{e2}}_{\text{increase after a decrease}}$  then  $g_{c2} \leftarrow g_{c1}$ ,  $g_{c1} \leftarrow (g_e - g_{e1})$

Cumulating energy increase continues.

if  $\underbrace{g_e > g_{e1} \text{ and } g_{e1} > g_{e2}}_{\text{increase after an increase}}$  then  $g_{c1} \leftarrow g_{c1} + (g_e - g_{e1})$

Otherwise  $g_e \leq g_{e1}$ , thus cumulating energy increase stops, and  $g_{c1}$  is memorized.

### Pseudo programmatoid solution

$$\begin{aligned} g_{c1} &= g_{c1} - H(g_{e2} - g_{e1}) g_{c1} + H(g_e - g_{e1}) (g_e - g_{e1}) \\ g_{c2} &= g_{c2} + H(H(g_e - g_{e1}) + H(g_{e2} - g_{e1}) - 3/2) (g_{c1} - g_{c2}) \end{aligned}$$

which is not a pure programmatoid solution because, because of term of the form  $H(u)v$ , thus with a product, but is implementable in the neuronoid framework discussed in the sequel. In brief:

$$H(u) v \simeq h(v/v + v h(v u) - v)$$

where  $h(\cdot)$  is the sigmoid function, and  $v$  a sufficiently large member.

### 1.2.2 Navigation

**Heuristic** : The bot runs at constant velocity,

(i) ahead by default, thanks to a linear correction, high enough to correct the direction, small enough to avoid oscillations, and

(ii) attempts to perform a quarter-turn in the preferred orientation as soon as passing is detected.

With this navigation mechanism the bot performs either leftward or rightward half-loops, traversing the central corridor.

**Internal variable**

$$q_p \in \{0_{\text{leftward}}, 1_{\text{rightward}}\}, \quad q_p|_{t=0} = 0 \quad \text{Preferred quarter-turn direction.}$$

**Programmatoid solution** :

$$\begin{aligned} d_o &\leftarrow \underbrace{\gamma(p_l - p_r)}_{\text{linear correction to maintain direction ahead}} + \underbrace{\alpha(t_l - t_r)}_{\text{quarter-turn left or right}} \\ t_l &\leftarrow (1 - q_p) H(\beta - p_l) = H((\beta - p_l) - v q_p) \\ t_r &\leftarrow q_p H(\beta - p_r) = H((\beta - p_r) - v(1 - q_p)) \end{aligned}$$

where:

$$\begin{aligned} w &\simeq 1/4 && \text{Rough estimation of the path-width.} \\ \gamma &= \frac{5}{w/2} && \text{Saturates the correction at } 5^\circ \text{ if the depth difference is half of the path-width.} \\ \alpha &= 90 && \text{Saturates the correction at } \pm 90^\circ \text{ to make the quarter-turn, since the linear } |\gamma(p_l - p_r)| < 40 \text{ is lower than the quarter-turn term, the latter submut the former.} \\ \beta &= w && \text{Triggers the quarter-turn if the depth is higher than the path-width.} \\ v &= 10 && \text{Transform a boolean product to a step-function threshold.} \end{aligned}$$

while:

$$\begin{aligned} t_l &= 1 \quad \text{iff} \quad q_p = 0 \quad \text{and while} \quad \beta < p_l \\ t_r &= 1 \quad \text{iff} \quad q_p = 1 \quad \text{and while} \quad \beta < p_r \end{aligned}$$

in words: we execute the quater-turn until another wall is detected.

Regarding transforming a boolean product to a step-function threshold, we easily verify<sup>4</sup> that:

$$b \in \{0, 1\}, x \in ] - M, M[ \Rightarrow b H(x) = H(x - (1 - b) M),$$

for both values of  $b$ , while  $\max(|\beta - p_l|, |\beta - p_r|) \leq 1$ ; this is developed and generalized in the sequel.

<sup>4</sup>If  $b = 0$  then the equality writes  $0 = H(x - M)$ , but  $x < M$  so that  $H(x - M) = 0$ , thus verified, while if  $b = 1$  then the equality writes  $H(x) = H(x)$ , again verified.

We thus have a linear output unit for  $d_o$  and two step-unit for  $t_l$  and  $t_r$ .

### 1.2.3 Direction choices

#### 1.2.4 Task 1: Simple decision

**Strategy** Restrict navigation to the half-loop that contains the energy source, while the other does not.

**Heuristic** If the energy is too low, thus looping in the wrong direction, the direction is changed once.

At start  $q_p = 0$ . Then, if the energy is too low it changes once to  $q_p = 1$ .

$$q_p = \text{if } q_p = 1 \text{ or } \nu > g_e \text{ then } 1 \text{ else } 0$$

#### Programmatoid solution

$$q_p \leftarrow H(\nu q_p + (\nu - g_e))$$

where:

$c = 1/1000$	Energy consumption at each step.
$s = 1/100$	Speed: location increment at each steps.
$b = 3/2$	Distance bound between the starting point and the putative energy sources.
$\nu \simeq b c / s = 3/20$	Energy consumption threshold if no source on the path.

#### 1.2.5 Task 1b: Simple decision but varying environment

**Strategy** Restrict navigation to the half-loop that contains the energy source, while the other does not, this may change with time.

#### Heuristic

- If the energy is too low, the direction is inverted.
- This is registered, avoiding multiple changes at low energy.
- When the energy is high enough, change registration is reset.

#### Internal variable

$g_i \in \{0, 1\}$	$g_i _{t=0} = 0$	Detects the low energy, if not yet done.
$g_c \in \{0, 1\}$	$g_c _{t=0} = 0$	Registers if the low energy has been already detected.

#### Programmatoid solution

Detects if the direction is to be changed.

$$g_i \leftarrow \text{if } g_c = 0 \text{ and } \nu > g_e \text{ then } 1 \text{ else } 0 = \begin{aligned} &H(H(g_c - 1/2) \\ &+ H(g_e - \nu) - 3/2) \end{aligned}$$

Inverts the direction if to be changed.

$$q_p \leftarrow \text{if } g_i = 0 \text{ then } q_p \text{ else } 1 - q_p = \begin{aligned} &H(q_p - 1/2 - \nu(1 - g_i)) \\ &+ H(1/2 - q_p - \nu g_i) \end{aligned}$$

Registers the inversion until the energy is high enough.

$$g_c \leftarrow \begin{aligned} &\text{if } 2\nu < g_e \text{ then } 0 \\ &\text{elif } g_c = 1 \text{ then } 1 \text{ else } g_i \end{aligned} = H(g_i - 1/2 + \nu g_c - 2\nu H(g_e - 2\nu))$$

### 1.2.6 Task 2: Cued environment decision

**Strategy** Restrict navigation to the half-loop without a closed path, as indicated by a color that has already been seen once.

**Heuristic** Detect and store the first color blob, and choose to turn in the direction it appears again.

**Internal variable**

$$c_{p\bullet} \in \{0, 1\} \quad c_{p\bullet} i|_{t=0} = 0 \quad \text{Color}$$

### Programmatoid solution

Detect the cue, if not yet done

if  $c_p = 0$  and  $c_l \neq 0$  then  $c_p \leftarrow c_l$

if  $c_p = 0$  and  $c_r \neq 0$  then  $c_p \leftarrow c_r$

Set the direction according to the cue

if  $c_p \neq 0$  and  $c_l \neq 0$  and  $c_p = c_l$  then  $q_c \leftarrow 0$

if  $c_p \neq 0$  and  $c_r \neq 0$  and  $c_p = c_r$  then  $q_c \leftarrow 1$

Reset the cue at a certain energy decrease

if  $g_e < \kappa$  then  $c_p \leftarrow 0$

$$\text{blablab } c_{l\bullet} \in \{0, 1\}, \bullet \in \{b_{\text{blue}}, r_{\text{red}}\}$$