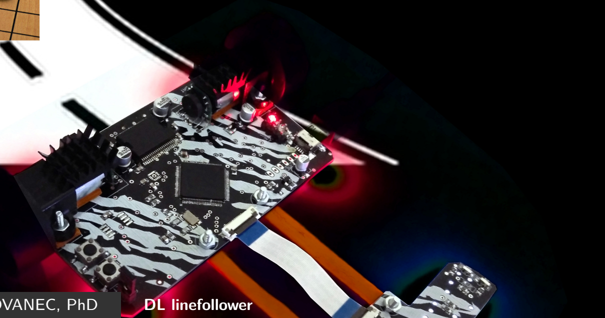
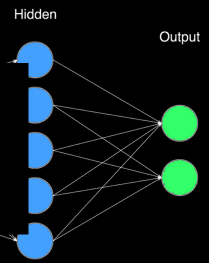
$$Q(s_t, a_t) \leftarrow \underbrace{Q(s_t, a_t)}_{\text{The New Action Value = The Old Value}} + \underbrace{\alpha}_{\text{The Learning Rate}} \Big[\underbrace{r_{t+1} + \lambda \max_{a} Q(s_{t+1}, a)}_{\text{The New Information}} - \underbrace{Q(s_t, a_t)}_{\text{the Old Information}} \Big]$$

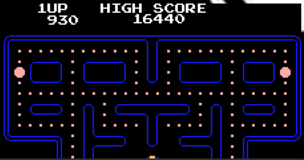
(The New Action Value = The Old Value) + The Learning Rate × (The New Information − the Old Information)



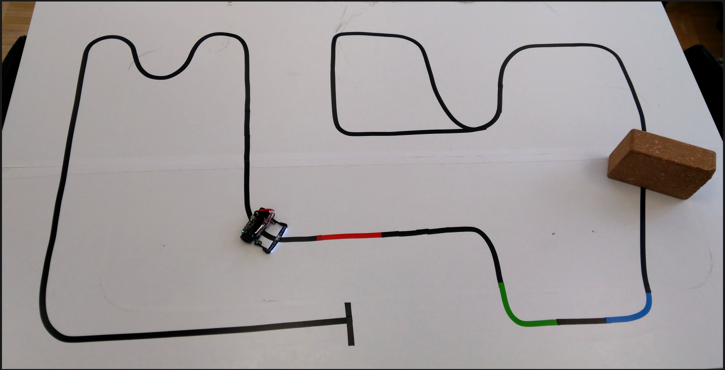


deep learning
for line following robot

Michal CHOVANEC



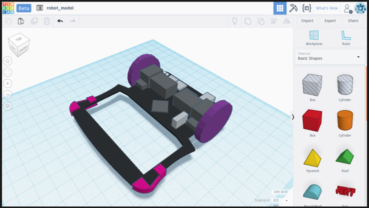
line follower competition

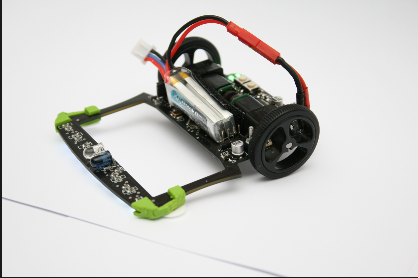


- SR - Istrobot
- CR - Roboticky den
- AU - Robot Challenge
- PL - Zawody robotow

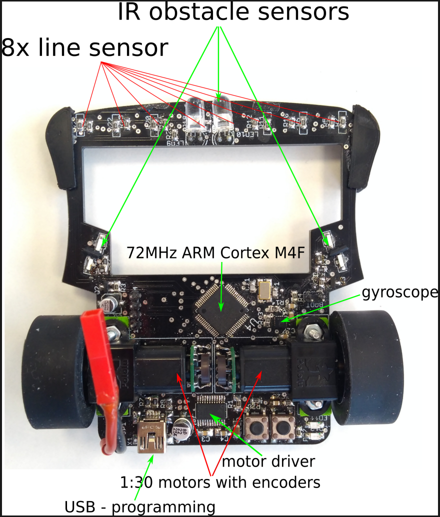
what does it take

- Hardware
  - strong light motors
  - high adhesion tyres
  - light accumulator
  - fast CPU
  - dozen of sensors
- Software
  - hard real time OS
  - tunned PIDs
  - predictive controll
  - mapping



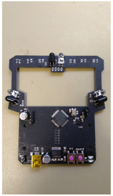


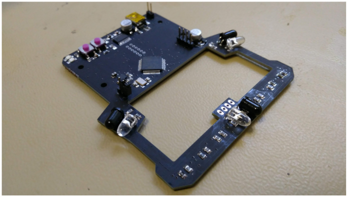
motoko uprising - hardware

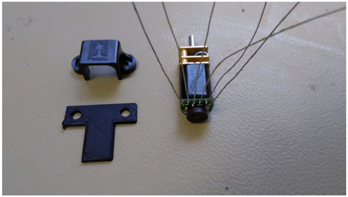


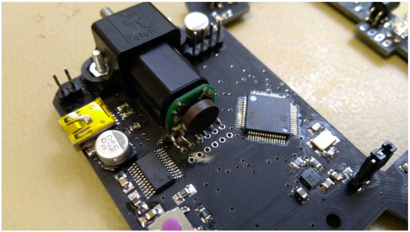
- **mcu** : STM32F303, 72MHz ARM Cortex M4F
- **motor driver** : TI DRV8834
- **motors** : 1:30 HP Pololu, with magnetic encoder
- **tyres** : Pololu 28mm diameter
- **line sensor** : 8x 540nm phototransistor + white LED
- **obstacle sensor** : SMD IR phototransistor + IR LED
- **imu** : LSM6DS0, gyroscope + accelerometer

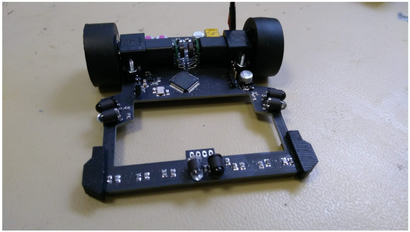
motoko uprising - hardware





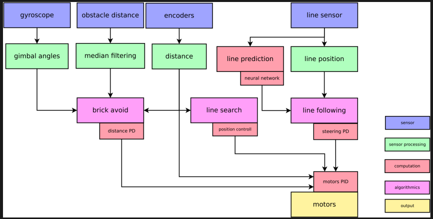




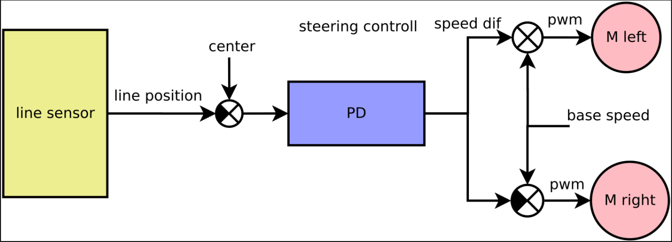


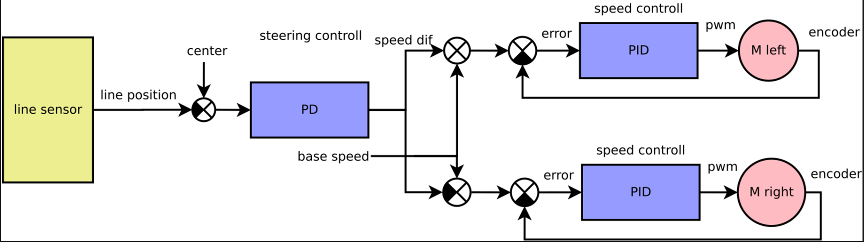
software

- **quadratic interpolation** : high precission line position computing
- **steering PID** : PD controller for steering
- **motor PID** : two PIDs for motors speed controll
- **curve shape prediction**
  - **fast** run on straight line, **brake** on curve
  - **deep neural network**
- written in **C++**
- **network training** on GPU - own framework for CNN

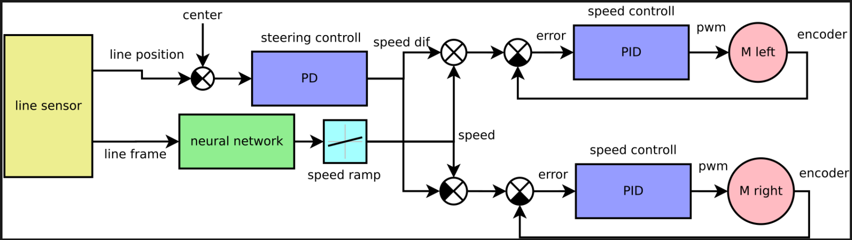


controll loop(s)



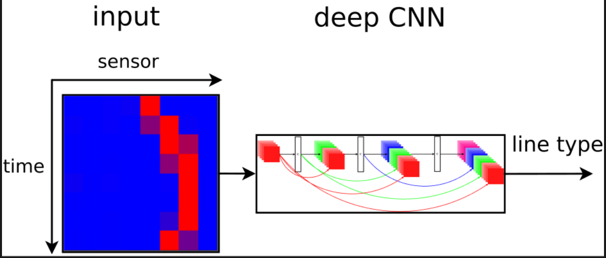


controll loop(s)

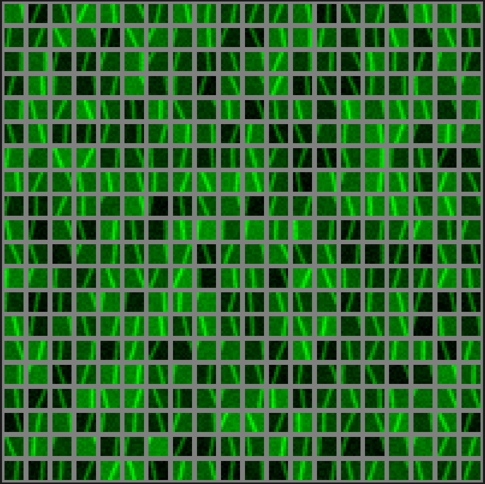


line shape prediction

- **fast** run on straight line, **brake** on curve
- **neural network** for line type classification
  - DenseNet - densely connected convolutional neural network
- **input** 8x8 matrix raw data from line sensors
  - 8 past line positions from 8 sensors
- **output** 5 curves types

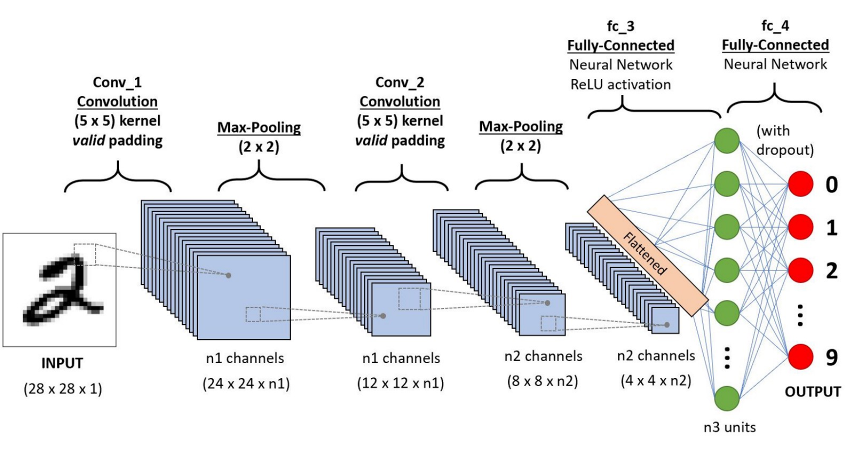


line dataset

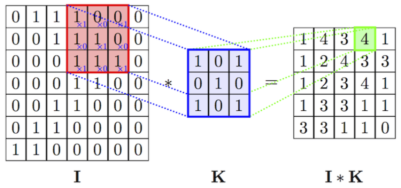


- 20000 for training
- 2500 for testing
- 8x8 inputs
- 5 outputs (5 curves types)
  - two left
  - one straight
  - two right
- augmentation - luma noise, white noise

convolutional neural network - CNN



discrete convolution



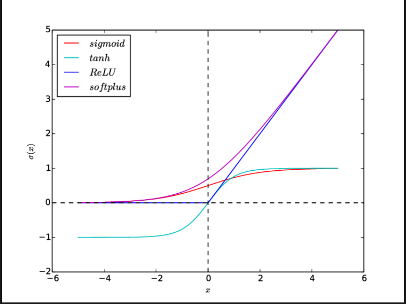

```
for (unsigned y = 0; y < input_height; y++)
for (unsigned x = 0; x < input_width; x++)
{
    float sum = 0.0;

    for (unsigned ky = 0; ky < kernel_height; ky++)
    for (unsigned kx = 0; kx < kernel_width; kx++)
    {
      sum+= kernel[ky][kx]*input[y + ky][x + kx];
    }

    output[y + kernel_height/2][x + kernel_width/2] = sum;
}
```

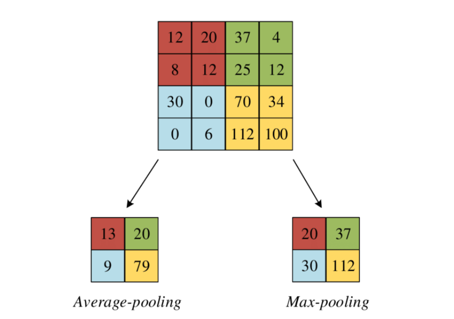
activation function

tanh, sigmoid, gaussian, **RELU**, leaky RELU ...



$$f(x) = \begin{cases} x & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases} \qquad \frac{df(x)}{dx} = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

pooling


12 20 37 4
8 12 25 12
30 0 70 34
0 6 112 100
13 20
9 79
Average-pooling
20 37
30 112
Max-pooling

target hardware

target	bits	features	frequency
AVR Atmega 328	8	single cycle ADD, MUL	20MHz
ARM Cortex M0	32	single cycle ADD, MUL	48MHz
ARM Cortex M4, M7	32	SIMD DUAL 16bit MAC , FPU ...	72MHz 216MHz

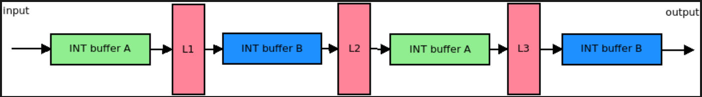
embedded network implementation

Quantization : convert float weights to int8_t

$$scale = max(|\vec{w}|_1)$$
$$\vec{w}' = \vec{w}\frac{127}{scale}$$

Memory saving : use double buffer memory trick

- unsigned buffer_size $=$ max$_i$(layers[i].input_size());
- buffer_a $=$ new int8_t(buffer_size);
- buffer_b $=$ new int8_t(buffer_size);



optimize kernel - templates

```
templete<unsigned int kernel_size>
void convolution()
{
  for (unsigned y = 0; y < input_height; y++)
  for (unsigned x = 0; x < input_width; x++)
  {
      int sum = 0;

      for (unsigned ky = 0; ky < kernel_size; ky++)
      for (unsigned kx = 0; kx < kernel_size; kx++)
      {
        sum+= kernel[ky][kx]*input[y + ky][x + kx];
      }

      output[y + kernel_size/2][x + kernel_size/2] = (sum*scale)/127;
  }
}

...

convolution<1>(); //1x1 kernel
convolution<3>(); //3x3 kernel
convolution<5>(); //5x5 kernel
```

optimize kernel - unrolling

```
templete<unsigned int kernel_size>
void convolution()
{
  for (unsigned y = 0; y < input_height; y++)
  for (unsigned x = 0; x < input_width; x++)
  {
      int sum = 0;

      if (kernel_size == 3)
      {
        sum+= kernel[0][0]*input[y + 0][x + 0];
        sum+= kernel[0][1]*input[y + 0][x + 1];
        sum+= kernel[0][2]*input[y + 0][x + 2];

        sum+= kernel[1][0]*input[y + 1][x + 0];
        sum+= kernel[1][1]*input[y + 1][x + 1];
        sum+= kernel[1][2]*input[y + 1][x + 2];

        sum+= kernel[2][0]*input[y + 2][x + 0];
        sum+= kernel[2][1]*input[y + 2][x + 1];
        sum+= kernel[2][2]*input[y + 2][x + 2];
      }

      output[y + kernel_size/2][x + kernel_size/2] = (sum*scale)/127;
  }
}
```

optimize kernel - SIMD instructions

elementary row MAC operation in 3x3 convolution :

- **sum**+= **kernel**[0][0]***input**[y + 0][x + 0];
- **sum**+= **kernel**[0][1]***input**[y + 0][x + 1];
- **sum**+= **kernel**[0][2]***input**[y + 0][x + 2];

instruction : SMLADX(int32_t val1, int32_t val2, int32_t val3)

- p1 = **val1**[15:0]***val2**[15:0]
- p2 = **val1**[31:16]***val2**[31:16]
- **res**[31:0] = p1 + p2 + **val3**[31:0]

speed up summary

convolutional	input size	kernels count	kernel size	computing time [ms]	speed up ratio
naive	16x16x16	16	1x1	109.8	1.00
naive	16x16x16	16	3x3	312	1.00
naive	16x16x16	16	5x5	532	1.00
template	16x16x16	16	1x1	26.6	4.13
template	16x16x16	16	3x3	213.6	1.46
template	16x16x16	16	5x5	373.3	1.43
template + unrolling	16x16x16	16	1x1	21	**5.23**
template + unrolling	16x16x16	16	3x3	57.1	**5.46**
template + unrolling	16x16x16	16	5x5	106.2	**5.01**

network results

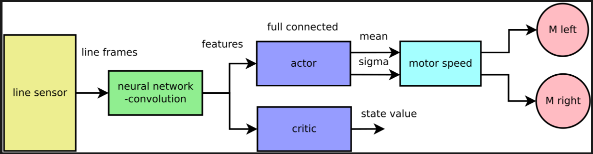
tiny architecture : IN8x8x1 - C3x3x4 - P2x2 - C3x3x8 - P2x2 - FC5
confussion matrix :

1029	12	0	0	0
14	**911**	18	0	0
0	21	**959**	6	0
0	0	21	**968**	18
0	0	0	11	**1012**
98.658	**96.504**	**96.092**	**98.274**	**98.252**

success count 4879
miss count 121
accuracy 97.58%

what is next?

reinforcement learning to take full controll -
Advatage Actor Critic - A2C

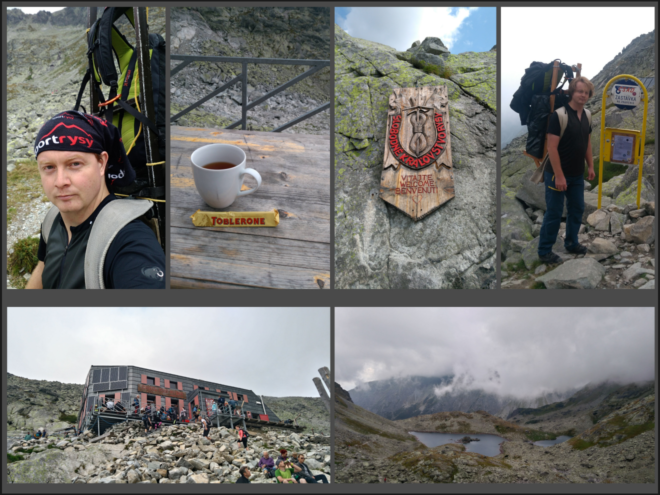


$$\mathcal{L}_{actor} = -(R(n) + \gamma Q(s(n+1); \phi) - Q(s(n); \phi))\, log\pi(s, a; \theta)$$

$$\mathcal{L}_{critic} = (R(n) + \gamma Q(s(n+1); \phi) - Q(s(n); \phi))^2$$

$$\mathcal{L}_{entropy} = \sum_a \pi(s, a; \theta) log\pi(s, a; \theta)$$

Q&A



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