KU LEUVEN
FACULTEIT INGENIEURSWETENSCHAPPEN

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LEUVEN

Model identification and learning control in autonomous driving

Identification of comfort parameters during lane change.

Eindwerk voorgedragen tot het behalen van het diploma van Master of Science in de ingenieurswetenschappen, richting Werktuigkunde, optie Voertuigtechnieken

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Voorwoord

Dank u mama, dank u papa, en dankuwel mijn lief.

Abstract

1 tot twee bladzijden over uw thesis

Contents

List of symbols

π	het getal pi
42	The Answer to the Ultimate Question of Life, the Universe, and Everything [**?**]

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Chapter 1

Inleiding

Algorithm 1: Learning rate

Result: $\boldsymbol{\theta}_{opti}$
initialization:
$\boldsymbol{\theta} = [1, 1, ..., 1, 1]$
$\boldsymbol{\theta} = \frac{\boldsymbol{\theta}}{norm_2(\boldsymbol{\theta})}$
$\tilde{\boldsymbol{f}} = \frac{1}{m} \sum_{i=1}^{m} \boldsymbol{f}(\boldsymbol{r}_{obs})$;
while *Not converged* **do**
  start opti:
  $\boldsymbol{r}_{exp,i} = argmin(\boldsymbol{\theta}^T \cdot \boldsymbol{f}(\boldsymbol{r})), \forall i \in 1 : m;$
  constraints:
    $opti.time = fixed\_time;$
    $opti.begin = initial(observed_i);$
    $opti.end = [y = lane\_distance, vy = 0, ay = 0, jy = 0];$
  end
  $E_{p(\boldsymbol{r}|\boldsymbol{\theta})}(\boldsymbol{f}) = \frac{1}{m} \sum_{i=1}^{m} \boldsymbol{f}(\boldsymbol{r}_{exp,i})$;
  $\Delta\boldsymbol{\theta} = \alpha \cdot (E_{p(\boldsymbol{r}|\boldsymbol{\theta})}(\boldsymbol{f}) - \tilde{\boldsymbol{f}});$
  $\boldsymbol{\theta} = \boldsymbol{\theta} + \Delta\boldsymbol{\theta};$
  $\boldsymbol{\theta} = \frac{\boldsymbol{\theta}}{norm_2(\boldsymbol{\theta})};$
  if $\Delta\boldsymbol{\theta} \leq \epsilon$ **then**
    $return(\boldsymbol{\theta});$
  end
end

Algorithm 2: Double optimization

Result: $\boldsymbol{\theta}_{opti}$
initialization:
$\boldsymbol{\theta} = [\frac{1}{nf}, \frac{1}{nf}, ..., \frac{1}{nf}, \frac{1}{nf}]$, nf: number of features
$\tilde{\boldsymbol{f}} = \frac{1}{m} \sum_{i=1}^{m} \boldsymbol{f}(\boldsymbol{r}_{obs})$;
while *Not converged* **do**
  start opti 1:
  $\boldsymbol{r}_{exp,i} = argmin(\boldsymbol{\theta}^T \cdot \boldsymbol{f}(\boldsymbol{r})), \forall i \in 1 : m;$
  constraints:
    $opti_1.time = fixed\_time;$
    $opti_1.begin = initial(observed_i);$
    $opti_1.end = [y = lane\_distance, vy = 0, ay = 0, jy = 0];$
  end
  $E_{p(\boldsymbol{r}|\boldsymbol{\theta})}(\boldsymbol{f}) = \frac{1}{m} \sum_{i=1}^{m} \boldsymbol{f}(\boldsymbol{r}_{exp,i})$;
  start opti 2:
  $\Delta\boldsymbol{\theta} = argmin \sum_{i=1}^{nf} -\Delta\theta_i \cdot (f(\boldsymbol{r}_{exp})_i - \tilde{f}_i);$
  constraints:
    $opti_2.subject\_to(\Delta\theta_i \cdot (f(\boldsymbol{r}_{exp})_i - \tilde{f}_i) \geq 0)$;
    $opti_2.subject\_to(\sum_{i=1}^{nf} \Delta\theta_i == 0)$;
  end
  $\boldsymbol{\theta} = \boldsymbol{\theta} + \Delta\boldsymbol{\theta};$
  if $\Delta\boldsymbol{\theta} \leq \epsilon$ **then**
    $return(\boldsymbol{\theta});$
  end
end

Figure 1.1: Dit is de sedes van de kul. Der staat trouwens bij dat de KUL in 1425 ontstaan is. Deze caption is uitzonderlijk lang om te testen ofdat het werkt om de caption over twee lijnen te zetten op 0.8 tekstbreedte.

Algorithm 3: Update theta

Result: $\boldsymbol{\theta}_{new}$
$\Delta\boldsymbol{\theta} = [0, 0...0]$;
for i = *[1...nf]* **do**
  if $\boldsymbol{f_{diff}}[i] > 0$ **then**
    $\Delta\boldsymbol{\theta}[i] = \Delta\boldsymbol{\theta}[i] + \boldsymbol{f_{diff}}[i]$
  else
    for k = *[1...nf]* **do**
      if *k!=i* **then**
        $\Delta\boldsymbol{\theta}[i] = \Delta\boldsymbol{\theta}[i] - \boldsymbol{f_{diff}}[i]$
      end
    end
  end
end
$\boldsymbol{\theta} = \frac{\boldsymbol{\theta}}{norm_2(\boldsymbol{\theta})}$

Algorithm 4: MPC loop

$current\_state = intitial\_state\_system$;
$history\_state = current\_state$;
$get(current\_ref)$;
$calculated\_control = solve(OCP, current\_ref)$;
for $N_{simulations}$ **do**
  $history\_control = calculated\_control;$
  $current\_state = \boldsymbol{f}(history\_state, calculated\_control);$
  $get(current\_ref);$
  $set(initial\_guess) = previous\_solution;$
  $calculated\_control = solve(OCP, current\_ref, initial\_guess);$
  $history\_state = current\_state;$
end

Algorithm 5: Path generation

Result: $\boldsymbol{r}_{opti}$
Initialization:
$\boldsymbol{\theta} = [1, 1, ..., 1, 1]$ Objective:
$\boldsymbol{r}_{opti} = argmin(\boldsymbol{\theta}^T \cdot \boldsymbol{f}(\boldsymbol{r}))$;
Constraints:
$\dot{\boldsymbol{X}}(t) = \boldsymbol{f}(\boldsymbol{X}(t), \boldsymbol{u}(t))$;
$opti.time = T$;
$opti.begin = [vx = V, other\_states = 0]$;
$opti.end = [y = lane\_distance, vy = 0, ay = 0, jy = 0]$;

Chapter 2

Comfort features

2.1 Comfort features found in literature

2.2 Comfort features found out of simulation data

dfs ?

fds

Chapter 3

Vehicle model

3.1 Comparison

hhu fs ffe
[1] [2] [3] [4] [5]

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