

## **Control of vehicle platoons**

**Hans Zwart (University of Twente, TU/e)**

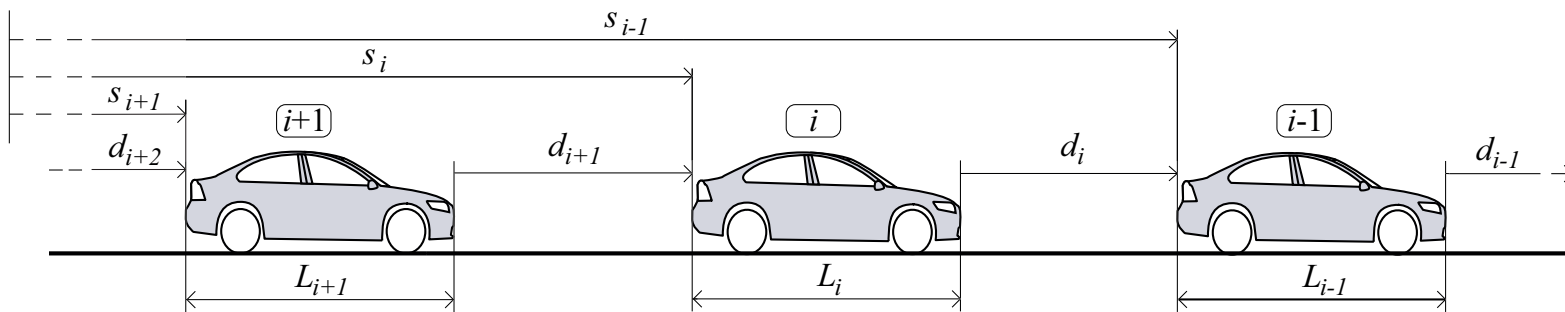
**joint work with:**

**Amir Firooznia (TU-Delft), Jeroen Ploeg (TNO), Nathan van de Wouw (TU/e)**

**Ruth Curtain and Orest Iftime (RUG)**

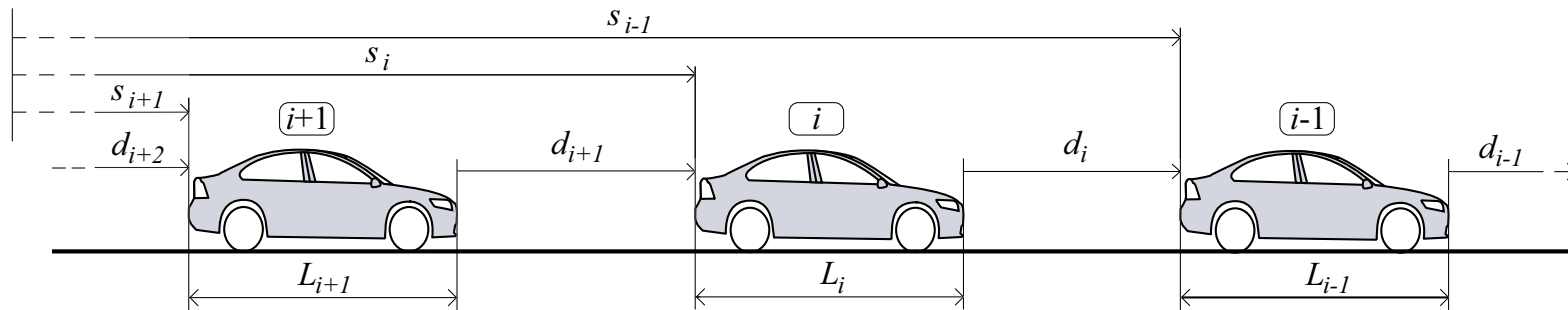
# 1 Introduction

Consider a string of vehicles (a platoon)



# 1 Introduction

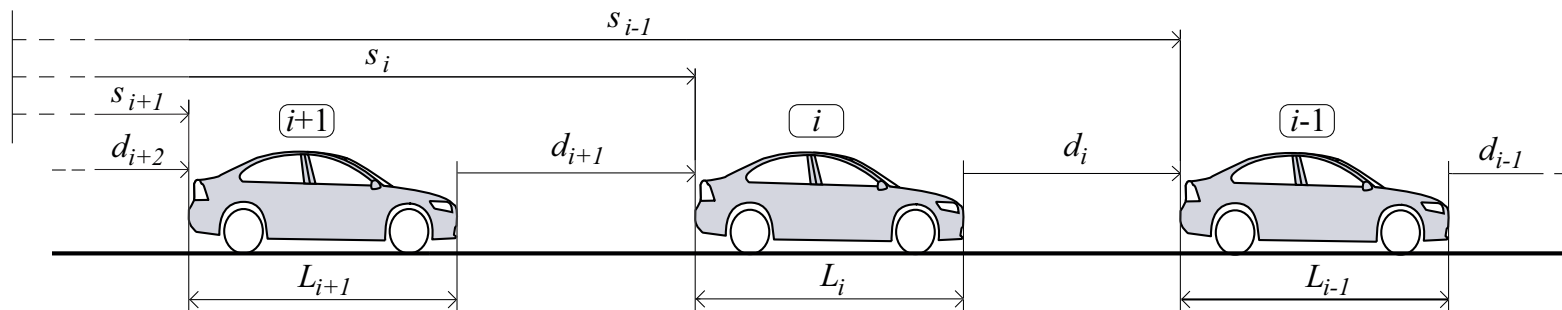
Consider a string of vehicles (a platoon)



The aim is to control the distance  $d_i$  between the cars. Every car controls its jerk, i.e, the change of its force.

# 1 Introduction

Consider a string of vehicles (a platoon)



The aim is to control the distance  $d_i$  between the cars. Every car controls its jerk, i.e, the change of its force.

Normally the (desired) distance has to satisfy  $d = d_0 + h * v$ , with  $v$  the velocity and  $h$  the headway time (0.3 – 1.2 s).

## Assumption

We will assume that we have an infinite string of identical vehicles, i.e.,  
 $i \in \mathbb{Z}$ .

## Assumption

We will assume that we have an infinite string of identical vehicles, i.e.,  
 $i \in \mathbb{Z}$ .

This assumption is motivated by

- A local controller will make different cars behave very similarly.

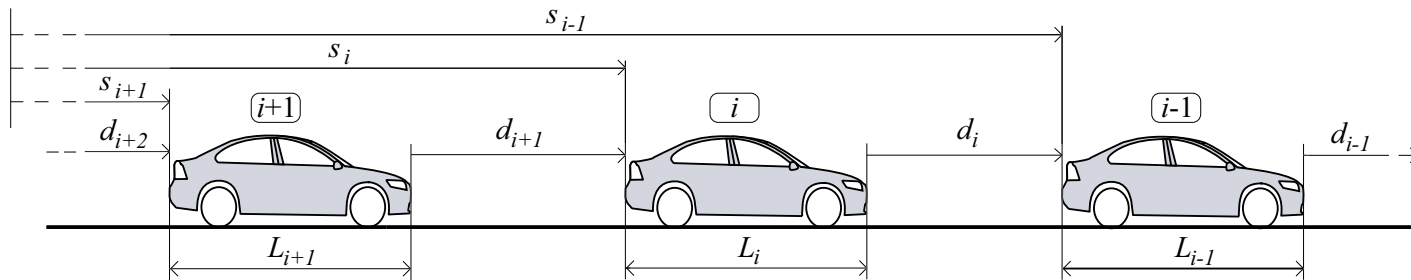
## Assumption

We will assume that we have an infinite string of identical vehicles, i.e.,  $i \in \mathbb{Z}$ .

This assumption is motivated by

- A local controller will make different cars behave very similarly.
- Large platoons must be similar to infinite platoons. (Folk theorem)

## 2 Model



Standard modeling gives the following model for the  $i$ 'th car

$$\frac{d}{dt} \begin{pmatrix} d_i(t) \\ v_i(t) \\ a_i(t) \end{pmatrix} = \begin{pmatrix} v_{i-1}(t) - v_i(t) \\ a_i(t) \\ -\tau^{-1}a_i(t) + \tau^{-1}u_i(t) \end{pmatrix}, \quad i \in \mathbb{Z}.$$

with  $d_i$  the distance,  $v_i$  the velocity,  $a_i$  the acceleration, and  $\tau$  a constant.



We want to track a constant distance  $C_{eq}$  and constant velocity  $v_{eq}$ . So we choose our state to be

$$\mathbf{x}_i(t) = \begin{pmatrix} x_{i,1}(t) \\ x_{i,2}(t) \\ x_{i,3}(t) \end{pmatrix} = \begin{pmatrix} d_i(t) - C_{eq} \\ v_i(t) - v_{eq} \\ a_i(t) \end{pmatrix}$$

With this state the model becomes

$$\frac{d}{dt}\mathbf{x}_i(t) = \begin{pmatrix} x_{i-1,2}(t) - x_{i,2}(t) \\ x_{i,3}(t) \\ -\tau^{-1}x_{i,3}(t) + \tau^{-1}u_i(t) \end{pmatrix}, \quad i \in \mathbb{Z}.$$

We want to track a constant distance  $C_{eq}$  and constant velocity  $v_{eq}$ . So we choose our state to be

$$\mathbf{x}_i(t) = \begin{pmatrix} x_{i,1}(t) \\ x_{i,2}(t) \\ x_{i,3}(t) \end{pmatrix} = \begin{pmatrix} d_i(t) - C_{eq} \\ v_i(t) - v_{eq} \\ a_i(t) \end{pmatrix}$$

With this state the model becomes

$$\frac{d}{dt} \mathbf{x}_i(t) = \begin{pmatrix} x_{i-1,2}(t) - x_{i,2}(t) \\ x_{i,3}(t) \\ -\tau^{-1} x_{i,3}(t) + \tau^{-1} u_i(t) \end{pmatrix}, \quad i \in \mathbb{Z}.$$

To design a control, i.e., find  $u_i$ , we apply the  $z$ -transform to this infinite set of differential equations.

## 2.1 $z$ -transform

The bilateral  $z$ -transformation transforms the sequence

$f := (f_k)_{k=-\infty}^{\infty}$  to the function  $\check{f}(z)$ , as

$$\check{f}(z) = (\mathcal{Z}(f))(z) = \sum_{k=-\infty}^{\infty} f_k z^{-k}, \quad z \in \partial\mathbb{D},$$

where  $\partial\mathbb{D}$  is the unit circle.

## 2.1 $z$ -transform

The bilateral  $z$ -transformation transforms the sequence

$f := (f_k)_{k=-\infty}^{\infty}$  to the function  $\check{f}(z)$ , as

$$\check{f}(z) = (\mathcal{Z}(f))(z) = \sum_{k=-\infty}^{\infty} f_k z^{-k}, \quad z \in \partial\mathbb{D},$$

where  $\partial\mathbb{D}$  is the unit circle.

It is well-known that the  $z$ -transform is an isometry between  $\ell^2(\mathbb{Z}; \mathbb{C}^n)$  (square summable sequences) and  $L^2(\partial\mathbb{D}; \mathbb{C}^n)$ , i.e.,

$$\sum_{k=-\infty}^{\infty} \|f_k\|^2 = \frac{1}{2\pi} \int_0^{2\pi} \|\check{f}(e^{i\theta})\|^2 d\theta.$$

Furthermore, the  $z$ -transform has the following nice property.

### Lemma

If  $g := (g_k)_{k=-\infty}^{\infty}$  is the shifted version of  $f$ , i.e.,  $g_k = f_{k-1}$ ,  $k \in \mathbb{Z}$ , then

$$\check{g}(z) = z^{-1} \check{f}(z), \quad z \in \partial\mathbb{D}.$$

## 2.2 Transformed system

Applying the  $z$ -transform to our system it becomes

$$\begin{aligned} \frac{d\check{x}}{dt}(z, t) &= \begin{pmatrix} 0 & z^{-1} - 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -\tau^{-1} \end{pmatrix} \check{x}(z, t) + \begin{pmatrix} 0 \\ 0 \\ \tau^{-1} \end{pmatrix} \check{u}(z, t) \\ &= \check{A}(z)\check{x}(z, t) + \check{B}(z)\check{u}(z, t). \end{aligned}$$

## 2.2 Transformed system

Applying the  $z$ -transform to our system it becomes

$$\begin{aligned} \frac{d\check{x}}{dt}(z, t) &= \begin{pmatrix} 0 & z^{-1} - 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -\tau^{-1} \end{pmatrix} \check{x}(z, t) + \begin{pmatrix} 0 \\ 0 \\ \tau^{-1} \end{pmatrix} \check{u}(z, t) \\ &= \check{A}(z)\check{x}(z, t) + \check{B}(z)\check{u}(z, t). \end{aligned}$$

Hence a parametrized finite-dimensional system on the state space

$$X = L^2(\partial\mathbb{D}; \mathbb{C}^3).$$

## 2.2 Transformed system

Applying the  $z$ -transform to our system it becomes

$$\begin{aligned} \frac{d\check{x}}{dt}(z, t) &= \begin{pmatrix} 0 & z^{-1} & -1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & -\tau^{-1} \end{pmatrix} \check{x}(z, t) + \begin{pmatrix} 0 \\ 0 \\ \tau^{-1} \end{pmatrix} \check{u}(z, t) \\ &= \check{A}(z)\check{x}(z, t) + \check{B}(z)\check{u}(z, t). \end{aligned}$$

Hence a parametrized finite-dimensional system on the state space

$$X = L^2(\partial\mathbb{D}; \mathbb{C}^3).$$

The multiplication operators  $\check{A}$  and  $\check{B}$  are bounded linear operators from  $X$  to  $X$ .



## 2.2 Transformed system

Applying the  $z$ -transform to our system it becomes

$$\begin{aligned} \frac{d\check{x}}{dt}(z, t) &= \begin{pmatrix} 0 & z^{-1} - 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -\tau^{-1} \end{pmatrix} \check{x}(z, t) + \begin{pmatrix} 0 \\ 0 \\ \tau^{-1} \end{pmatrix} \check{u}(z, t) \\ &= \check{A}(z)\check{x}(z, t) + \check{B}(z)\check{u}(z, t). \end{aligned}$$

Hence a parametrized finite-dimensional system on the state space

$$X = L^2(\partial\mathbb{D}; \mathbb{C}^3).$$

The multiplication operators  $\check{A}$  and  $\check{B}$  are bounded linear operators from  $X$  to  $X$ . For this transformed system we study the control problems.

# 3 Stability and Stabilization

## Definition

Consider the differential equation for  $z \in \partial\mathbb{D}$  and  $t \geq 0$

$$\frac{d\check{x}}{dt}(z, t) = \check{A}(z)\check{x}(z, t), \quad \check{x}(z, 0) = \check{x}_0(z).$$

## Definition

Consider the differential equation for  $z \in \partial\mathbb{D}$  and  $t \geq 0$

$$\frac{d\check{x}}{dt}(z, t) = \check{A}(z)\check{x}(z, t), \quad \check{x}(z, 0) = \check{x}_0(z).$$

It is exponentially stable, when there exists a  $M, \omega > 0$  such that

$$\|e^{\check{A}(\cdot)t}\| \leq Me^{-\omega t}.$$

## Definition

Consider the differential equation for  $z \in \partial\mathbb{D}$  and  $t \geq 0$

$$\frac{d\check{x}}{dt}(z, t) = \check{A}(z)\check{x}(z, t), \quad \check{x}(z, 0) = \check{x}_0(z).$$

It is exponentially stable, when there exists a  $M, \omega > 0$  such that

$$\|e^{\check{A}(\cdot)t}\| \leq Me^{-\omega t}.$$

It is strongly or asymptotically stable, when for all initial conditions  $\check{x}_0$

$$\|e^{\check{A}(\cdot)t}\check{x}_0\| \rightarrow 0.$$

## Definition

Consider the differential equation for  $z \in \partial\mathbb{D}$  and  $t \geq 0$

$$\frac{d\check{x}}{dt}(z, t) = \check{A}(z)\check{x}(z, t), \quad \check{x}(z, 0) = \check{x}_0(z).$$

It is exponentially stable, when there exists a  $M, \omega > 0$  such that

$$\|e^{\check{A}(\cdot)t}\| \leq Me^{-\omega t}.$$

It is strongly or asymptotically stable, when for all initial conditions  $\check{x}_0$

$$\|e^{\check{A}(\cdot)t}\check{x}_0\| \rightarrow 0.$$

Can we characterize these properties point-wise?

**Assume that  $z \in \partial\mathbb{D} \mapsto \check{A}(z) \in \mathbb{C}^{n \times n}$  is continuous.**

### Theorem

**The differential equation  $\frac{d}{dt}\check{x}(t) = \check{A}\check{x}(t)$  is exponentially stable if and only if  $\check{A}(z)$  is Hurwitz for all  $z \in \partial\mathbb{D}$ .**

Assume that  $z \in \partial\mathbb{D} \mapsto \check{A}(z) \in \mathbb{C}^{n \times n}$  is continuous.

### Theorem

The differential equation  $\frac{d}{dt}\check{x}(t) = \check{A}\check{x}(t)$  is exponentially stable if and only if  $\check{A}(z)$  is Hurwitz for all  $z \in \partial\mathbb{D}$ .

Furthermore, it is strongly/asymptotically stable if and only if

- For almost every  $z \in \partial\mathbb{D}$  the (matrix) exponential  $\left(e^{\check{A}(z)t}\right)_{t \geq 0}$  is exponentially stable, and
- $\text{ess sup}_{t \geq 0, z \in \partial\mathbb{D}} \left\| e^{\check{A}(z)t} \right\| < \infty$ .



Assume that  $z \in \partial\mathbb{D} \mapsto \check{A}(z) \in \mathbb{C}^{n \times n}$  is continuous.

### Theorem

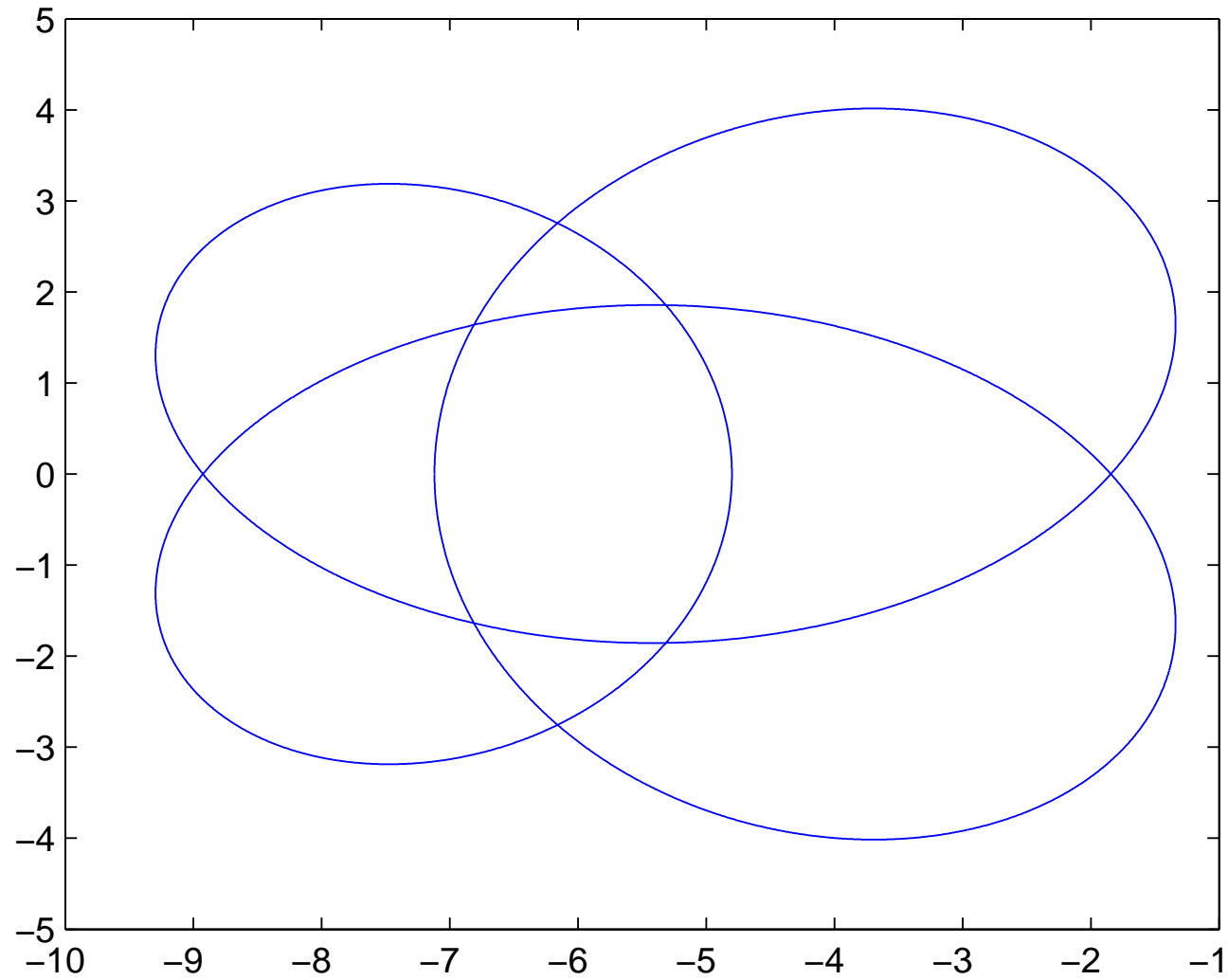
The differential equation  $\frac{d}{dt}\check{x}(t) = \check{A}\check{x}(t)$  is exponentially stable if and only if  $\check{A}(z)$  is Hurwitz for all  $z \in \partial\mathbb{D}$ .

Furthermore, it is strongly/asymptotically stable if and only if

- For almost every  $z \in \partial\mathbb{D}$  the (matrix) exponential  $\left( e^{\check{A}(z)t} \right)_{t \geq 0}$  is exponentially stable, and
- $\text{ess sup}_{t \geq 0, z \in \partial\mathbb{D}} \left\| e^{\check{A}(z)t} \right\| < \infty$ .

The second item is hard to check, but there are sufficient conditions.

The spectrum of  $\check{A}$  typically looks something like this.



### 3.1 Exponential stabilizability

Motivated by our platoon model we consider the differential equation for  $z \in \partial\mathbb{D}$  and  $t \geq 0$

$$\frac{d\check{x}}{dt}(z, t) = \check{A}(z)\check{x}(z, t) + \check{B}(z)\check{u}(z, t), \quad \check{x}(z, 0) = \check{x}_0(z).$$

Here  $\check{u}$  is the control signal. This we denote as the system  $\Sigma(\check{A}, \check{B}, -)$ .

### 3.1 Exponential stabilizability

Motivated by our platoon model we consider the differential equation for  $z \in \partial\mathbb{D}$  and  $t \geq 0$

$$\frac{d\check{x}}{dt}(z, t) = \check{A}(z)\check{x}(z, t) + \check{B}(z)\check{u}(z, t), \quad \check{x}(z, 0) = \check{x}_0(z).$$

Here  $\check{u}$  is the control signal. This we denote as the system  $\Sigma(\check{A}, \check{B}, -)$ .

We assume that  $\check{A}(\cdot)$  and  $\check{B}(\cdot)$  are continuous functions on the unit circle  $\partial\mathbb{D}$ .

### Definition

The system  $\Sigma(\check{A}, \check{B}, -)$  is exponentially stabilizable if there exists an  $\check{F}$  such that  $\check{A} + \check{B}\check{F}$  is exponentially stable.

Hence the control  $\check{u}(z, t) = \check{F}(z)\check{x}(z, t)$  makes the system exponentially stable.

### Definition

The system  $\Sigma(\check{A}, \check{B}, -)$  is exponentially stabilizable if there exists an  $\check{F}$  such that  $\check{A} + \check{B}\check{F}$  is exponentially stable.

Hence the control  $\check{u}(z, t) = \check{F}(z)\check{x}(z, t)$  makes the system exponentially stable.

### Theorem

The system  $\Sigma(\check{A}, \check{B}, -)$  is exponentially stabilizable if and only if for all  $z \in \partial\mathbb{D}$  the finite-dimensional system  $\Sigma(\check{A}(z), \check{B}(z), -)$  is exponentially stabilizable.

## Example

For our system we have that

$$\check{A}(z) = \begin{pmatrix} 0 & z^{-1} - 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -\tau^{-1} \end{pmatrix}, \quad \check{B}(z) = \begin{pmatrix} 0 \\ 0 \\ \tau^{-1} \end{pmatrix}.$$

For  $z = 1$  not exponentially stabilizable (always eigenvalue zero), and so  $\Sigma(\check{A}, \check{B}, -)$  is not exponentially stabilizable.

# 4 Linear Quadratic Optimal Control



Consider the system  $\Sigma(\check{A}, \check{B}, \check{C})$

$$\begin{aligned}\frac{d\check{x}}{dt}(t) &= \check{A}\check{x}(t) + \check{B}\check{u}(t), \quad \check{x}(0) = \check{x}_0 \\ \check{y}(t) &= \check{C}\check{x}(t),\end{aligned}$$

with  $\check{B} \in \mathcal{L}(U, X)$  and  $\check{C} \in \mathcal{L}(X, Y)$ , where  $U$  and  $Y$  are Hilbert spaces.

Consider the system  $\Sigma(\check{A}, \check{B}, \check{C})$

$$\begin{aligned}\frac{d\check{x}}{dt}(t) &= \check{A}\check{x}(t) + \check{B}\check{u}(t), \quad \check{x}(0) = \check{x}_0 \\ \check{y}(t) &= \check{C}\check{x}(t),\end{aligned}$$

with  $\check{B} \in \mathcal{L}(U, X)$  and  $\check{C} \in \mathcal{L}(X, Y)$ , where  $U$  and  $Y$  are Hilbert spaces.

To this system we associate the following cost criterion

$$J(\check{x}_0, \check{u}) = \int_0^\infty \|\check{y}(t)\|^2 + \|\check{u}(t)\|^2 dt.$$

Consider the system  $\Sigma(\check{A}, \check{B}, \check{C})$

$$\begin{aligned}\frac{d\check{x}}{dt}(t) &= \check{A}\check{x}(t) + \check{B}\check{u}(t), \quad \check{x}(0) = \check{x}_0 \\ \check{y}(t) &= \check{C}\check{x}(t),\end{aligned}$$

with  $\check{B} \in \mathcal{L}(U, X)$  and  $\check{C} \in \mathcal{L}(X, Y)$ , where  $U$  and  $Y$  are Hilbert spaces.

To this system we associate the following cost criterion

$$J(\check{x}_0, \check{u}) = \int_0^\infty \|\check{y}(t)\|^2 + \|\check{u}(t)\|^2 dt.$$

The following general theorem holds:

## Theorem

For the system  $\Sigma(\check{A}, \check{B}, \check{C})$  with cost criterion  $J(\check{x}_0, \check{u})$  the following are equivalent.

- The system is optimizable, i.e., for every  $\check{x}_0 \in X$  there exists an input  $\check{u}$  such that  $J(\check{x}_0, \check{u}) < \infty$ .

## Theorem

For the system  $\Sigma(\check{A}, \check{B}, \check{C})$  with cost criterion  $J(\check{x}_0, \check{u})$  the following are equivalent.

- The system is optimizable, i.e., for every  $\check{x}_0 \in X$  there exists an input  $\check{u}$  such that  $J(\check{x}_0, \check{u}) < \infty$ .
- For every  $\check{x}_0 \in X$  there exists an (unique) input  $\check{u}^{\text{opt}}$  such that  $J(\check{x}_0, \check{u}^{\text{opt}}) \leq J(\check{x}_0, \check{u})$  for all  $\check{u}$ .

## Theorem

For the system  $\Sigma(\check{A}, \check{B}, \check{C})$  with cost criterion  $J(\check{x}_0, \check{u})$  the following are equivalent.

- The system is optimizable, i.e., for every  $\check{x}_0 \in X$  there exists an input  $\check{u}$  such that  $J(\check{x}_0, \check{u}) < \infty$ .
- For every  $\check{x}_0 \in X$  there exists an (unique) input  $\check{u}^{\text{opt}}$  such that  $J(\check{x}_0, \check{u}^{\text{opt}}) \leq J(\check{x}_0, \check{u})$  for all  $\check{u}$ .
- There exists a non-negative solution to the ARE:

$\check{P} \in \mathcal{L}(X)$ ,  $\check{P} \geq 0$  and

$$\check{A}^* \check{P} + \check{P} \check{A} - \check{P} \check{B} \check{B}^* \check{P} + \check{C}^* \check{C} = 0.$$

## Theorem

For the system  $\Sigma(\check{A}, \check{B}, \check{C})$  with cost criterion  $J(\check{x}_0, \check{u})$  the following are equivalent.

- The system is optimizable, i.e., for every  $\check{x}_0 \in X$  there exists an input  $\check{u}$  such that  $J(\check{x}_0, \check{u}) < \infty$ .
- For every  $\check{x}_0 \in X$  there exists an (unique) input  $\check{u}^{\text{opt}}$  such that  $J(\check{x}_0, \check{u}^{\text{opt}}) \leq J(\check{x}_0, \check{u})$  for all  $\check{u}$ .
- There exists a non-negative solution to the ARE:

$$\check{P} \in \mathcal{L}(X), \check{P} \geq 0 \text{ and}$$

$$\check{A}^* \check{P} + \check{P} \check{A} - \check{P} \check{B} \check{B}^* \check{P} + \check{C}^* \check{C} = 0.$$

If one of the above holds, then  $\check{u}^{\text{opt}} = -\check{B}^* \check{P} \check{x}$ .

**As for stability we can formulate this theorem point-wise.**



**As for stability we can formulate this theorem point-wise.**

### Theorem

**For the system  $\Sigma(\check{A}, \check{B}, \check{C})$  with cost-function  $J(\check{x}_0, \check{u})$  the following are equivalent:**

- 1. The system is optimizable;**
- 2. For almost all  $z \in \partial\mathbb{D}$ , the Algebraic Riccati Equation (ARE)**

$$\check{A}^*(z)\check{P}(z) + \check{P}(z)\check{A}(z) - \check{P}(z)\check{B}(z)\check{B}^*(z)\check{P}(z) + \check{C}^*(z)\check{C}(z) = 0$$

**possesses a non-negative solution  $\check{P}(z)$  and**  
 **$\text{ess sup}_{z \in \partial\mathbb{D}} \|\check{P}(z)\| < \infty$ .**

**The condition  $\text{ess sup}_{z \in \partial \mathbb{D}} \|\check{P}(z)\| < \infty$  does not necessarily hold even when  $\Sigma(\check{A}(z), \check{B}(z), \check{C}(z))$  is optimizable for all  $z \in \partial \mathbb{D}$ .**

The condition  $\text{ess sup}_{z \in \partial \mathbb{D}} \|\check{P}(z)\| < \infty$  does not necessarily hold even when  $\Sigma(\check{A}(z), \check{B}(z), \check{C}(z))$  is optimizable for all  $z \in \partial \mathbb{D}$ .

### Example

Consider the following system

$$\check{A}(z) = 1 - z, \quad \check{B}(z) = (-1 + z)^2, \quad \check{C}(z) = -1 + z.$$

Since for  $z \in \partial \mathbb{D}$ ,  $z \neq 1$ , the real part of  $\check{B}(z)$  is non-zero, for such  $z$  the (finite-dimensional) system is exponentially stabilizable and hence optimizable.

The condition  $\text{ess sup}_{z \in \partial \mathbb{D}} \|\check{P}(z)\| < \infty$  does not necessarily hold even when  $\Sigma(\check{A}(z), \check{B}(z), \check{C}(z))$  is optimizable for all  $z \in \partial \mathbb{D}$ .

### Example

Consider the following system

$$\check{A}(z) = 1 - z, \quad \check{B}(z) = (-1 + z)^2, \quad \check{C}(z) = -1 + z.$$

Since for  $z \in \partial \mathbb{D}$ ,  $z \neq 1$ , the real part of  $\check{B}(z)$  is non-zero, for such  $z$  the (finite-dimensional) system is exponentially stabilizable and hence optimizable.

For  $z = 1$ ,  $\Sigma(\check{A}(z), \check{B}(z), \check{C}(z)) = \Sigma(0, 0, 0)$ . This implies that  $J(\check{x}_0(0), 0) = 0$ , and hence the system is optimizable for all  $z$ .

Solving the ARE gives with  $z = e^{i\theta}$ ,  $\theta \in [0, 2\pi)$

$$\begin{aligned}\check{P}(z) &= \frac{1 - \cos(\theta) + \sqrt{(1 - \cos(\theta))^2 + 8(1 - \cos(\theta))^3}}{(2 - 2\cos(\theta))^2} \\ &= \frac{1 + \sqrt{1 + 8(1 - \cos(\theta))}}{4(1 - \cos(\theta))}\end{aligned}$$

Since now  $\check{P}(z)$  is unbounded on the unit circle, the optimal control problem is not solvable for this system.

## Remark

- If  $\check{C} = I$ , then optimizability is equivalent to exponential stabilizability.
- Normally, the optimizability is checked by checking exponential stabilizability.
- Our system is not exponentially stabilizable. Hence if we want to solve the optimal control problem we have to choose the  $\check{C}$  carefully. Moreover, point-wise optimizability is necessary.

## Lemma

Consider the system  $\Sigma(\check{A}, \check{B}, \check{C})$  with cost functional  $J(\check{x}_0, \check{u})$ . Furthermore, assume that  $\check{A}$ ,  $\check{B}$ , and  $\check{C}$  are continuously depending on  $z \in \partial\mathbb{D}$ . If the system is optimizable, then for every  $z \in \partial\mathbb{D}$ , the finite-dimensional system  $\Sigma(\check{A}(z), \check{B}(z), \check{C}(z))$  is optimizable.

## 4.1 Our platoon model

For our system we have that

$$\check{A}(z) = \begin{pmatrix} 0 & z^{-1} - 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -\tau^{-1} \end{pmatrix}, \quad \check{B}(z) = \begin{pmatrix} 0 \\ 0 \\ \tau^{-1} \end{pmatrix}.$$



## 4.1 Our platoon model

For our system we have that

$$\check{A}(z) = \begin{pmatrix} 0 & z^{-1} - 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -\tau^{-1} \end{pmatrix}, \quad \check{B}(z) = \begin{pmatrix} 0 \\ 0 \\ \tau^{-1} \end{pmatrix}.$$

By (analytical) computations, we could prove that the system is optimizable for

$$\check{C}(z) = \begin{pmatrix} 1 - z & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}.$$

**Furthermore, the optimal control, i.e.,**

$$\check{u}^{\text{opt}}(z, t) = -\check{B}(z)^* \check{P}(z) \check{x}^{\text{opt}}(z, t)$$

**is strongly/asymptotically stabilizing the system.**

## 4.2 Another output

For our system with

$$\check{C}(z) = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 - z & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

we could not prove analytically that it is optimizable. However, numerical calculations showed it.

Furthermore, the optimal control is strongly/asymptotically stabilizing the system.

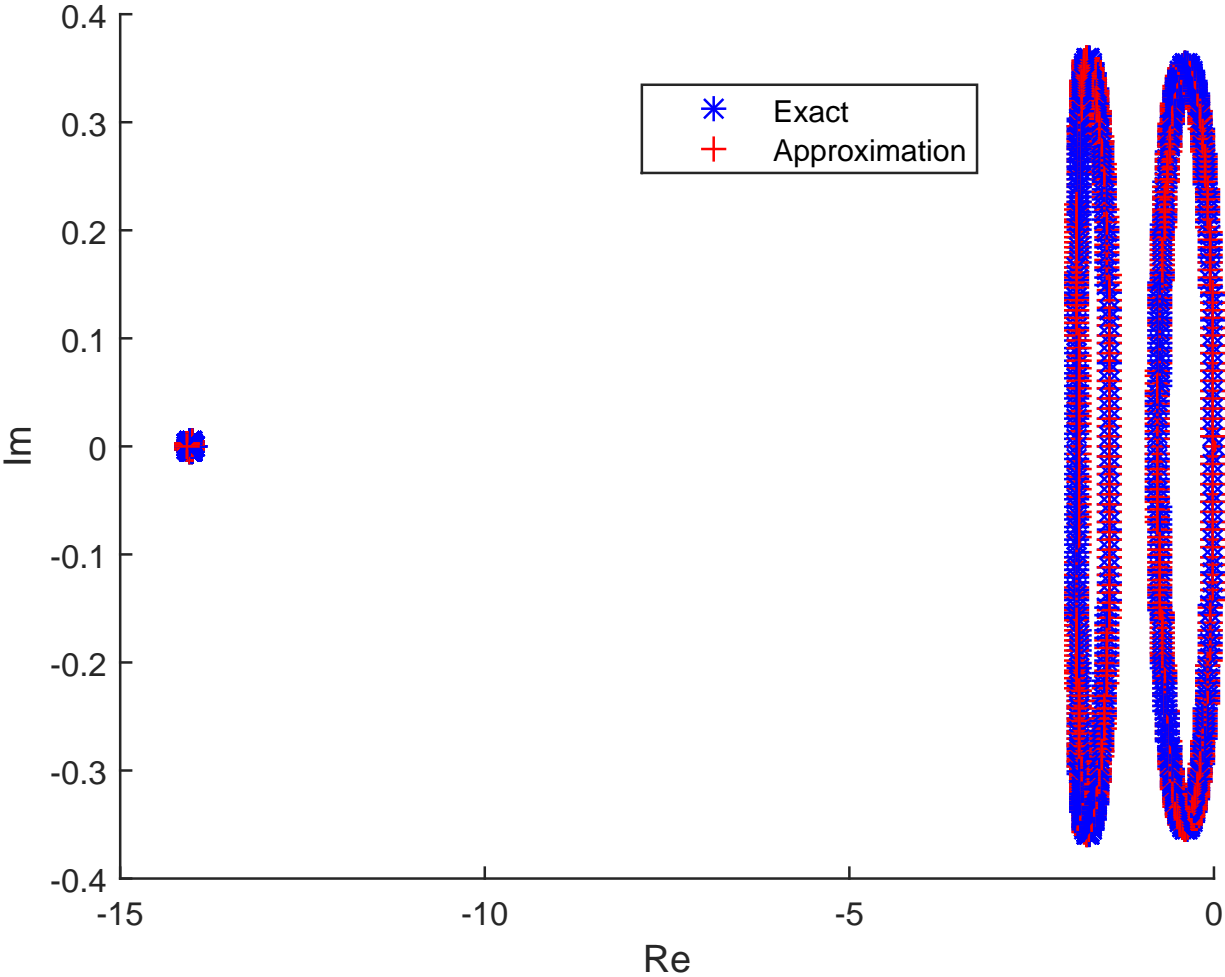
## 4.2 Another output

For our system with

$$\check{C}(z) = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 - z & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

we could not prove analytically that it is optimizable. However, numerical calculations showed it.

Furthermore, the optimal control is strongly/asymptotically stabilizing the system. Approximation in “vehicle-index” gives similar results (4 look-ahead/4 look-behind).



**Figure 1: Spectrum of the closed loop system**

## 5 Open problems

- Find easy checkable (sufficient) conditions for optimizability.
- Find easy checkable (sufficient) conditions for which the optimal control strongly stabilizes the system.
- Find easy checkable (sufficient) conditions for (strongly) stabilizability, i.e., when does there exist a  $\check{F}$  such that differential associated to  $\check{A} + \check{B}\check{F}$  is strongly stable.
- What is stability?

## 5.1 Stable or not?

Consider the following example

$$\frac{dx_i}{dt}(t) = -x_i(t) + x_{i-1}(t), \quad i \in \mathbb{Z} \quad (1)$$

After  $z$ -transformation this becomes

$$\frac{d\check{x}}{dt}(z, t) = (-1 + z^{-1})\check{x}(z, t), \quad z \in \partial\mathbb{D}. \quad (2)$$

It is not hard to see that this is strongly/asymptotically stable.

## 5.1 Stable or not?

Consider the following example

$$\frac{dx_i}{dt}(t) = -x_i(t) + x_{i-1}(t), \quad i \in \mathbb{Z} \quad (1)$$

After  $z$ -transformation this becomes

$$\frac{d\check{x}}{dt}(z, t) = (-1 + z^{-1})\check{x}(z, t), \quad z \in \partial\mathbb{D}. \quad (2)$$

It is not hard to see that this is strongly/asymptotically stable.

Define now  $v(t) = \sum_{i \in \mathbb{Z}} x_i(t)$ , then by the differential equation (1) we find

$$\dot{v}(t) = 0.$$

So not stable.



**Question?**