LPV control approaches for vehicle dynamics

Olivier Sename

ICMCE 2020, Roma, Italy

Grenoble, France, Capital of French Alps

Grenoble INP
UNIVERSITÉ Grenoble Alpes

61 000 students (9000 foreigners)
(~1 400 engineering diplomas / year)

3 500 PhD Students
7 000 faculty staff/researchers

THE "FRENCH SILICON VALLEY" (25000 PUBLIC AND PRIVATE RESEARCHERS) & THE WORLD'S 5^{th} MOST INVENTIVE CITY FORBES RANKING 2013

Outline

Smart and autonomous vehicles: connected, safer, and comfortable

Important stakes

- reduce road fatalities, traffic jams, CO_2
- allow everyone to travel regarless of its abilities
- enhance in-car passenger experiences

Automated vehicles towards self-driving cars

- Driver supervision: ESP, CACC, Lane Keeping
- Unsupervised: Traffic Jam Chauffeur, Valet parking, Highway pilot with platooning...

Figure: *Renault's goal: make riding in cars it more pleasant, less stressful and more productive* © Groupe Renault 2019

Smart and autonomous vehicles: connected, safer, and comfortable

Important stakes

- reduce road fatalities, traffic jams, CO_2
- allow everyone to travel regarless of its abilities
- enhance in-car passenger experiences

Automated vehicles towards self-driving cars

- Driver supervision: ESP, CACC, Lane Keeping
- Unsupervised: Traffic Jam Chauffeur, Valet parking, Highway pilot with platooning...

Future cars: many technical challenges

- deal with many sensors/actuators : middle range cars with around 1000 sensors and 100 small actuators
- increased software/hardware complexity: how to synchronize & monitor all the intelligent organs for performance and reliability?

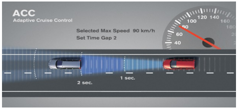
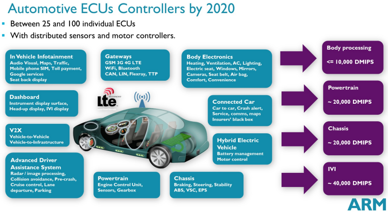


Figure: *Renault's goal: make riding in cars it more pleasant, less stressful and more productive* © Groupe Renault 2019



What is an LPV system?

Definition of an Linear Parameter Varying system

$$\Sigma(\rho) : \left[\begin{array}{c} \dot{x} \\ \hline z \\ y \end{array}\right] = \left[\begin{array}{c|cc} A(\rho) & B_1(\rho) & B_2(\rho) \\ \hline C_1(\rho) & D_{11}(\rho) & D_{12}(\rho) \\ C_2(\rho) & D_{21}(\rho) & D_{22}(\rho) \end{array}\right] \left[\begin{array}{c} x \\ \hline w \\ u \end{array}\right]$$

$x(t) \in \mathbb{R}^n$, ..., $\rho = (\rho_1(t), \rho_2(t), \ldots, \rho_N(t)) \in \Omega$, is a vector of time-varying parameters (Ω convex set), assumed to be **known** $\forall t$

What is an LPV system?

Definition of an Linear Parameter Varying system

$$\Sigma(\rho):\begin{bmatrix}\dot{x}\\ \hline z\\ y\end{bmatrix}=\left[\begin{array}{c|cc}A(\rho) & B_1(\rho) & B_2(\rho)\\ \hline C_1(\rho) & D_{11}(\rho) & D_{12}(\rho)\\ C_2(\rho) & D_{21}(\rho) & D_{22}(\rho)\end{array}\right]\begin{bmatrix}x\\ \hline w\\ u\end{bmatrix}$$

$x(t)\in\mathbb{R}^n$, ..., $\rho=(\rho_1(t),\rho_2(t),\dots,\rho_N(t))\in\Omega$, is a vector of time-varying parameters (Ω convex set), assumed to be **known** $\forall t$

Example (Scherer, ACC Tutorial 2012)

Dampened mass-spring system:

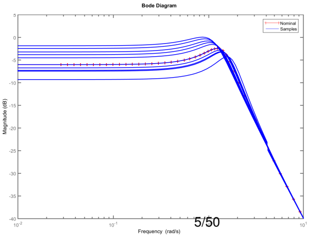
$$\ddot{p}+c\,\dot{p}+k(t)\,p=u,\quad y=x$$

First-order state-space representation:

$$\frac{d}{dt}\begin{pmatrix}p\\ \dot{p}\end{pmatrix}=\begin{pmatrix}0 & 1\\ -k(t) & -c\end{pmatrix}\begin{pmatrix}p\\ \dot{p}\end{pmatrix}+\begin{pmatrix}0\\ 1\end{pmatrix}u,$$

$$y=\begin{pmatrix}1 & 0\end{pmatrix}\begin{pmatrix}p\\ \dot{p}\end{pmatrix}$$

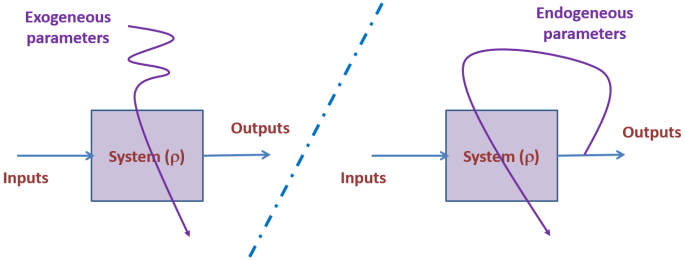
The frozen Bode plots for $c=1$ and $k\in[1,3]$



About the parameters

The parameters ρ are always assumed to be **known** (or measurable) and **bounded**:

$$\rho_i(t) \in [\underline{\rho_i},\ \overline{\rho_i}],\quad \forall i \tag{1}$$



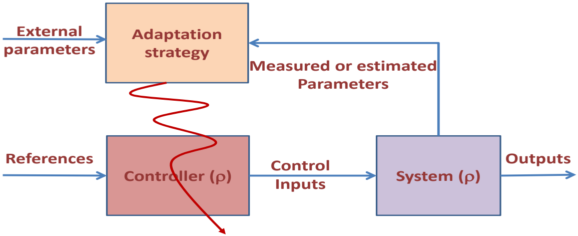
Exogenous parameters = external variables. The system is therefore *non stationary*.
See the previous damped mass-spring system.

Endogenous parameters : $\rho = \rho(x(t), t)$
Case of **quasi-LPV systems**: approximation of non-linear systems.

$$\dot{x}(t) = x^2(t) = \rho(t)x(t) \text{ with } \rho(t) = x(t)$$

Towards LPV control Apkarian, Scherer, Wu ....

The "self-scheduling" approach



Usual LPV control problems: H_∞ and/or H_2

Find a LPV controller $C(\rho)$ s.t the closed-loop system $\mathcal{CL}(\rho)$

- is stable, (quadratic or parameter-dependent stability)
- satisfies an H_∞ and/or H_2 performance: frequency-domain specifications through filters

Some LMI solutions: polytopic, LFT, SOS, gridding

LPV approach=linear or nonlinear? (Shamma, Apkarian & Gahinet, Balas & Seiler, Grigoriadis ...)

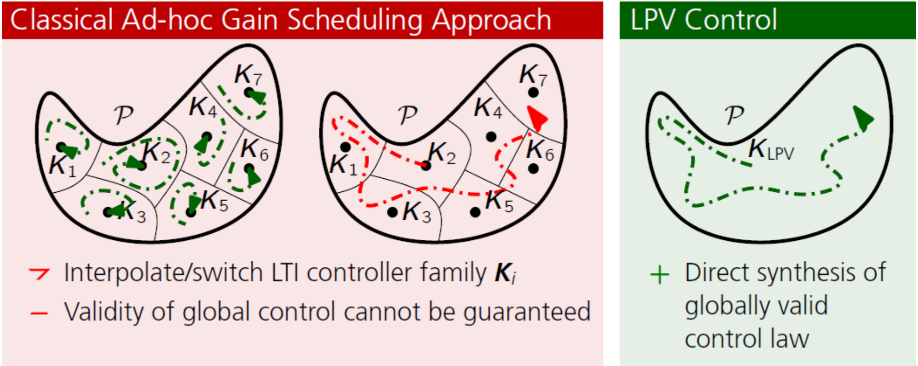
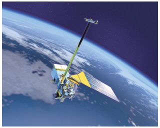


Figure: DLR German Aerospace Center (ESA LPV Workshop 2014)

LPV approach and applications

Aerospace

Marcos, Balas, Seiler, Biannic



Benani, Falcoz

Automotive

Gaspar Poussot, Doumiati ,

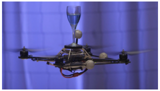
Werner, Mohammadpour, Zhu

Some recent books

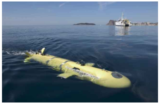
J. Mohammadpour, C. Scherer, (Eds), Control of Linear Parameter Varying Systems with Applications, Springer-Verlag New York, 2012.

O. Sename, P. Gaspar, J. Bokor (Eds), Robust Control and Linear Parameter Varying Approaches: Application to Vehicle Dynamics, Springer, 2013

Mechatronics, Robotics



Theilliol, Puig



Roche & Simon

Outline

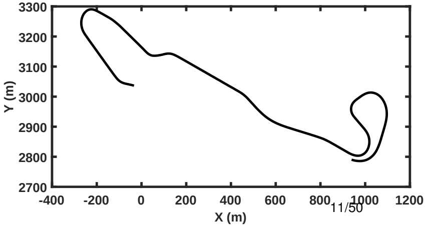
Control of autonomous vehicles

Mainly includes path planning, longitudinal control, lateral control

Steering control is a 'classical control' problem

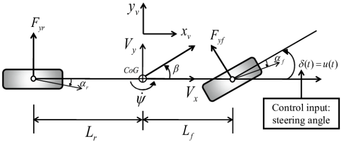
- many contribution for ADAS (MPC, H_∞, Sliding mode.....) Ackermann, Rajamani, Tseng, Mammar...
- recent studies for autonomous vehicles (Lane keeping, lane changing..) Gerdes, Borelli, Puig, Sentouh, Milanes
- Key issues: handle low/high speeds, ensures small lateral errors, accounts for varying look-ahead distance,

Collaboration: Renault : 2 co-supervised PhD thesis, Real car & trajectory



LPV modelling

2 wheels bicycle model



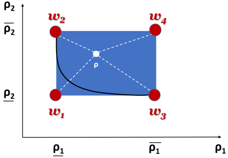
$$x(t) = \begin{bmatrix} v_y \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} \text{lateral acceleration} \\ \text{yaw rate} \end{bmatrix}$$

$$G(v_x) \begin{cases} \dot{x}(t) = A(v_x)x(t) + Bu(t) \\ y(t) = Cx(t) + Du(t) \end{cases}$$

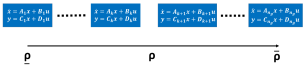
$$A(v_x) = \begin{bmatrix} -\frac{C_r+C_f}{mv_x} & -\frac{l_fC_f-l_rC_r}{mv_x} - v_x \\ -\frac{l_fC_f-l_rC_r}{Iv_x} & -\frac{l_f^2C_f+l_r^2C_r}{Iv_x} \end{bmatrix}$$

LPV simplified bicycle model : 3 approaches

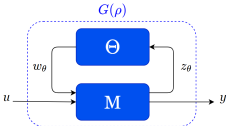
polytopic: $\rho_1 = v_x$, $\rho_2 = 1/v_x$



grid-based 40 grid points for $\rho = v_x \in [3, 40]m/s$

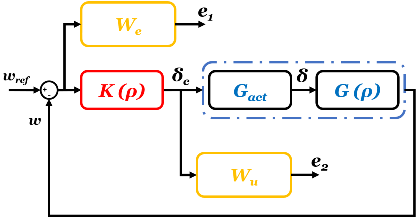


Linear Fractional Tranfsformation



LPV Control problem

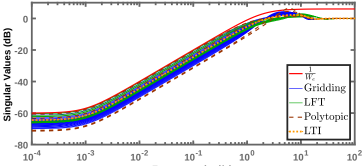
Control design scheme



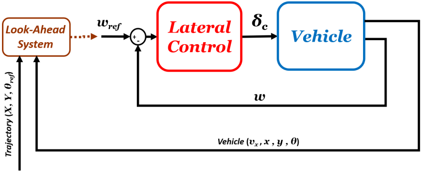
W_e : tracking performances, W_u actuator limitations

Analysis of the sensitivity Functions

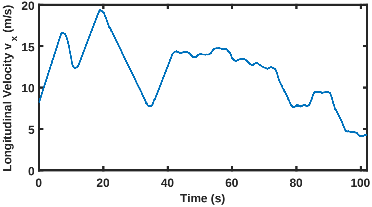
$$S = \frac{w_{ref} - w}{w_{ref}}$$



Control implementaiton scheme: experimental validation



Speed profile measured from a real test (m/s)



Experimental comparison

Experimental lateral error of the LTI and LPV controllers (m)

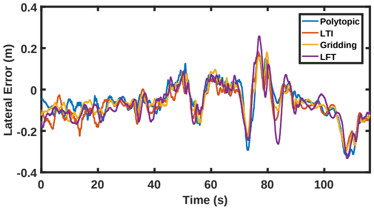


Table: RMS of the lateral error for experimental comparison

	Polytopic	LTI	Gridding	LFT
RMS	0.1473	0.1105	0.1025	0.1096

All controllers have good peformances in term of minimization of the lateral error

Experimental steering wheel angle of the LTI and LPV controllers (rad)

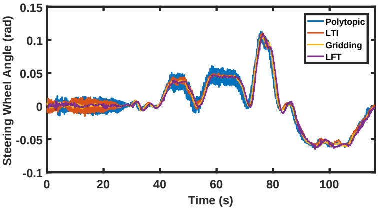


Table: RMS of the steering wheel rate for experimental comparison

	Polytopic	LTI	Gridding	LFT
RMS	0.0263	0.0149	0.0107	0.0129

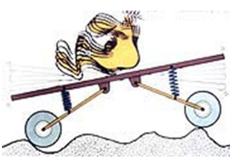
The grid-based and LFT controllers provide smooth steering control. The polytopic and the LTI controllers are sensitive to noises, especially at high speeds (when $t \leq 60\ s$)

Outline

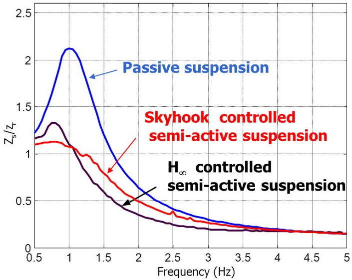
A key component: intelligent suspensions

Why?

- Comfort: mitigate the road-induced vibrations: human sensitivity (0 - 20 Hz)
- Road holding: limit the wheel rebound
- Road handling: limit the roll & pitch motions



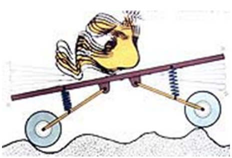
Frequency-domain objectives (Bode)



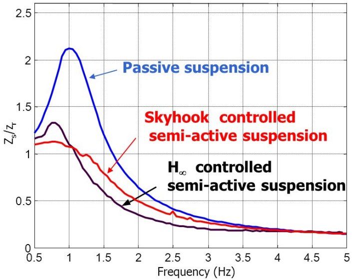
A key component: intelligent suspensions

Why?

- Comfort: mitigate the road-induced vibrations: human sensitivity (0 - 20 Hz)
- Road holding: limit the wheel rebound
- Road handling: limit the roll & pitch motions



Frequency-domain objectives (Bode)



Many studies

A. Zin, C. Poussot-Vassal, S. Aubouet, J. Lozoya, A-L Do, S. Fergani, J-C Tudon, M-Q Nguyen, D. Hernandez, C. Vivas, T-P Pham, K. Murali, M. Menezes.

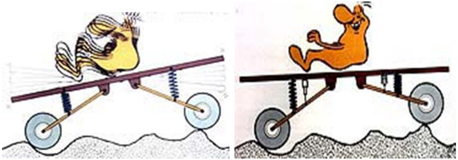
ANR INOVE (2010-2015) Soben mips

TECNOLÓGICO DE MONTERREY MTA SZTAKI COMPUTER AND AUTOMATION RESEARCH INSTITUTE HUNGARIAN ACADEMY OF SCIENCES POLITECNICO DI MILANO

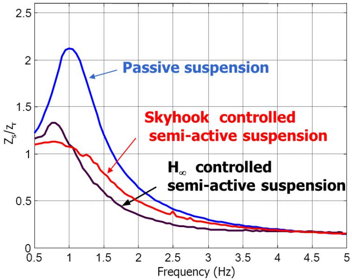
A key component: intelligent suspensions

Why?

- Comfort: mitigate the road-induced vibrations: human sensitivity (0 - 20 Hz)
- Road holding: limit the wheel rebound
- Road handling: limit the roll & pitch motions



Frequency-domain objectives (Bode)



Many studies

A. Zin, C. Poussot-Vassal, S. Aubouet, J. Lozoya, A-L Do, S. Fergani, J-C Tudon, M-Q Nguyen, D. Hernandez, C. Vivas, T-P Pham, K. Murali, M. Menezes.

ANR INOVE (2010-2015) Soben mips

TECNOLÓGICO DE MONTERREY MTA SZTAKI COMPUTER AND AUTOMATION RESEARCH INSTITUTE HUNGARIAN ACADEMY OF SCIENCES POLITECNICO DI MILANO

What happens in case of a damper loss of efficiency?

- Performance deterioration
- State-Of-Health decrease
- Force saturation (poor control)
- $\hookrightarrow$ FTC interest

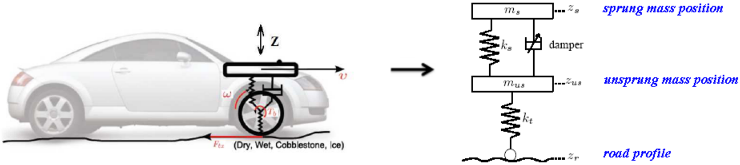


Figure: Simple quarter vehicle model for semi-active suspension control

Quarter vehicle dynamics

$$\begin{cases} m_s \ddot{z}_s &= -k_s z_{def} - F_{damper} \\ m_{us} \ddot{z}_{us} &= k_s z_{def} + F_{damper} - k_t (z_{us} - z_r) \end{cases} \quad (2)$$

$z_{def} = z_s - z_{us}$: damper deflection, $\dot{z}_{def} = \dot{z}_s - \dot{z}_{us}$: deflection velocity.

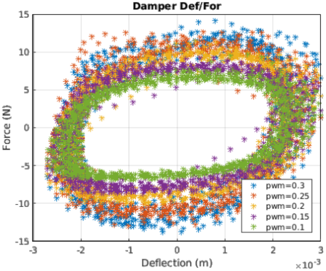
- The damper's characteristics : Force-Deflection-Deflection Velocity relation

$$F_{damper} = g\left(z_{def}, \dot{z}_{def}\right) \quad (3)$$

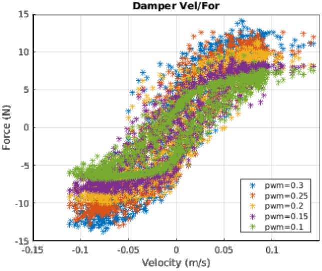
where g can be linear or nonlinear.

Electro-Rheological (ER) semi-active dampers -GIPSA

Force-Displacement map



Force-Velocity map

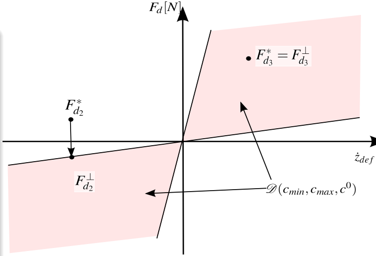


A semi-active damper phenomenological model

NON LINEAR MR/ER damper model (Guo)

$$F_{damper} = \underbrace{c_0 \dot{z}_{def} + k_0 z_{def}}_{\text{passive}} + \underbrace{d_c \cdot \tanh\left(c_1 \dot{z}_{def} + k_1 z_{def}\right)}_{\text{semi-active=controlled}}$$

- $\tanh$: represents the bi-viscous behavior.
- d_c: control input (current I or voltage V).
  $0 \le d_{cmin} \le d_c \le d_{cmax}$ - passivity constraint.
  (d_{cmin}=soft damper, d_{cmax}=hard damper).



A Key issue

handle the semi-active constraint through an LPV model based approach with a non-linear damper model (for estimation and/or control) - CEP'08, Annu. Rev. Control'12, Systol'13

What about faulty damper ?

In case of oil leakage, deformation, power supply loss, or State-Of-Health decrease:

$$\overline{F}_{damper} = \alpha F_{damper}$$

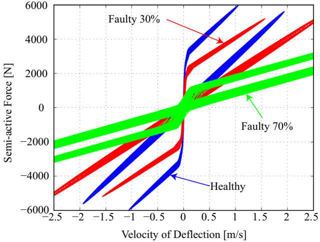
$\alpha \in [0, 1]$ is the loss of efficiency coefficient.

Issue: how to estimate α ?

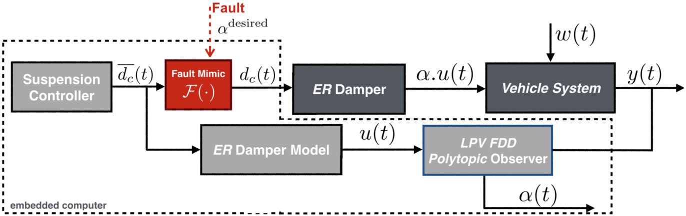
$$\Downarrow$$

LPV formulation with $\rho = F^{model}_{damper} = u(t)$

Force-Velocity map of a semi-active damper (low and high damping) subject to different leakages.



An LPV observer for damper fault estimation (Cont. Eng. Pract. 2019)



H_2/H_∞ *LPV* observer for fault estimation (Cont. Eng. Pract. 2019)

Extended LPV model

Assumption: Knowledge of a road profile model ($w_{\text{m}}(t)$) (IEEE TCST2015 & CEP 2017)

$$\dot{x}_a(t) = \mathbf{A}_a(\rho)x_a(t) + \mathbf{B}_w\delta w(t) + \mathbf{B}_\nu \nu(t), \quad \text{with } x_a(t) = [x(t), \alpha(t), w_m(t)]$$

The chosen LPV observer:

$$\begin{aligned} \dot{\hat{x}}_a(t) &= \mathbf{A}_a(\rho)\hat{x}_a(t) + \mathbf{L}(\rho).[y(t) - \mathbf{C}_a(\rho)\hat{x}_a(t)] \\ \hat{\alpha}(t) &= \mathbf{E}\hat{x}_a(t) \end{aligned} \tag{4}$$

The mixed H_2/H_∞ *LPV* observer design problem

Find an LPV gain matrix $\mathbf{L}(\rho)$ so that the fault estimation error dynamics $e(t) = x_a(t) - \hat{x}_a(t)$) are exponentially stable when $\nu(t)$ and $\delta w(t)$ are null, and, such that the two following objective functions are minimized (concerning $e_\alpha(t) = \alpha(t) - \hat{\alpha}(t)$:

Noise attenuation $\quad J_{H_2} = ||\frac{e_\alpha}{\nu}||_2 \leq \gamma_{H_2}$ under $e(t)|_{t=0} = 0$ & $\delta w(t) \equiv 0$

Uncertainty minimization $\quad J_{H_\infty} = ||\frac{e_\alpha}{\delta w}||_\infty \leq \gamma_{H_\infty}$ under $e(t)|_{t=0} = 0$ & $\nu(t) \equiv 0$

H_2/H_∞ *LPV* observer for fault estimation (Cont. Eng. Pract. 2019)

Extended LPV model

Assumption: Knowledge of a road profile model ($w_{\text{m}}(t)$) (IEEE TCST2015 & CEP 2017)

$$\dot{x}_a(t) = \mathbf{A}_a(\rho)x_a(t) + \mathbf{B}_w\delta w(t) + \mathbf{B}_\nu \nu(t), \quad \text{with } x_a(t) = [x(t), \alpha(t), w_m(t)]$$

The chosen LPV observer:

$$\begin{aligned} \dot{\hat{x}}_a(t) &= \mathbf{A}_a(\rho)\hat{x}_a(t) + \mathbf{L}(\rho).[y(t) - \mathbf{C}_a(\rho)\hat{x}_a(t)] \\ \hat{\alpha}(t) &= \mathbf{E}\hat{x}_a(t) \end{aligned} \quad (4)$$

The mixed H_2/H_∞ *LPV* observer design problem

Find an LPV gain matrix $\mathbf{L}(\rho)$ so that the fault estimation error dynamics $e(t) = x_a(t) - \hat{x}_a(t)$) are exponentially stable when $\nu(t)$ and $\delta w(t)$ are null, and, such that the two following objective functions are minimized (concerning $e_\alpha(t) = \alpha(t) - \hat{\alpha}(t)$:

Noise attenuation	J_{H_2}	$=$	$\|\|\frac{e_\alpha}{\nu}\|\|_2 \leq \gamma_{H_2}$	under	$e(t)\|_{t=0} = 0$	&	$\delta w(t) \equiv 0$
Uncertainty minimization	J_{H_∞}	$=$	$\|\|\frac{e_\alpha}{\delta w}\|\|_\infty \leq \gamma_{H_\infty}$	under	$e(t)\|_{t=0} = 0$	&	$\nu(t) \equiv 0$

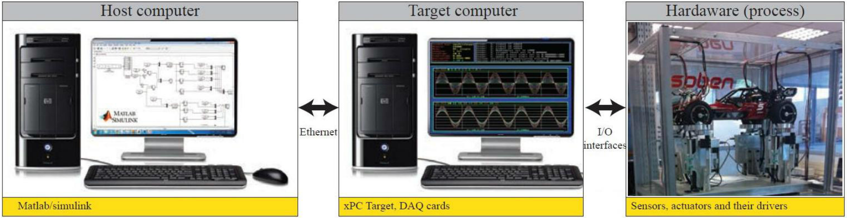
Experiments with GIPSA-lab/INOVE platform

Test bench

- The process: $1/5$ scaled real vehicle equipped with 4 Electro-Rheological semi-active dampers and 4 DC motors to generate the desired road profiles.
- Matlab/Simulink Real-Time Workshop environment for real time data acquisition and control.

Embedded algorithms

Real-time implementation of the LPV polytopic observer (on-line computation of a convex combination of LTI vertices observer) .



Validation Experimental scenario

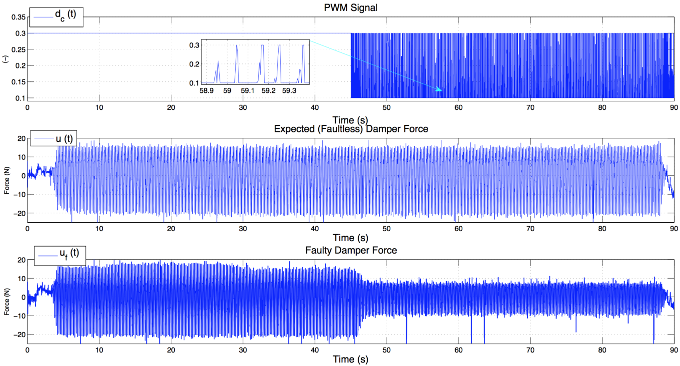
Scenario

Road profile= a sequence of sinusoidal speed bumps ($20\,\mathrm{mm}$ peak to peak), simulating a vehicle running at $120\,\mathrm{km/h}$ in a straight line on a dry road

constant *PWM* signal at $30\,\%$)

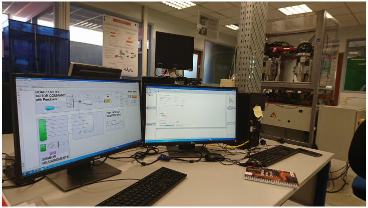
Expected (faultless) damper force

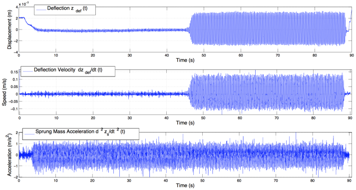
Faulty damper force. 50% loss of damper efficiency at $45sec.$



Experimental Validation Scenario: Expected and real faulty damper forces

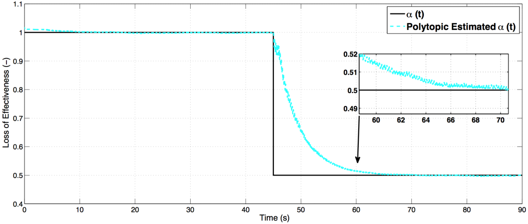
Estimation results





Measured Outputs: $z_{def}(t)$ and $\ddot{z}_s(t)$

Accurate estimation of the 50% damper loss of efficiency. Useful for local damper control, State-Of-Health monitoring



ER Damper Fault Estimation

Vehicle Dynamics Control for Safe driving

Leader: Olivier Sename

Michel Basset

Benjamin Talon

Brigitte d'Andréa-Novel

Projet ANR BLAN 0308

An Integrated Approach for Observation and Control of Vehicle Dynamics.

Outline

What about global chassis control approaches (GCC)?

What is GCC ?

- combines several (at least 2) subsystems in order to improve the vehicle global behavior Shibahata (2004)
- tends to make collaborate the different subsystems in view of the same objectives, according to the situation (constraints, environment, ...)
- is develop to improve comfort and safety, according to the driving situation, accounting for actuator constraints and to the eventual knowledge of the vehicle environment

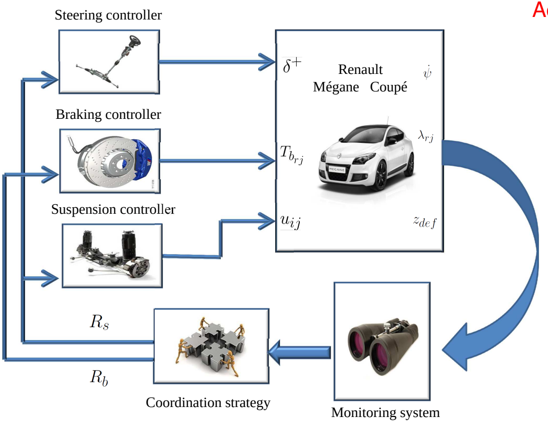
LPV interest: on-line Adaption of the vehicle performances

- to various road conditions/types (measured, estimated)
- to the driver actions
- to the dangers (vehicle on-board sensors)
- to actuators/sensors malfunctions or failures

Phd Students / Post Docs / Coll.

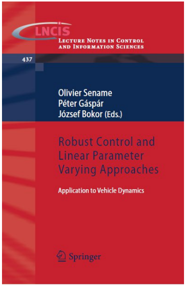
C. Poussot, S. Fergani, M. Doumiati. P. Gaspar & J. Bokor MTA SZTAKI COMPUTER AND AUTOMATION RESEARCH INSTITUTE HUNGARIAN ACADEMY OF SCIENCES

A proposed Global Chassis Control approach (IEEE TVT'16, IJRNC'17)



Actuators /On-board sensors :

- active braking et active steering: wheel rotational velocities, yaw rate, steering wheel angle, lateral acceleration
- (Semi-)active suspension : body and wheel vertical accelerations



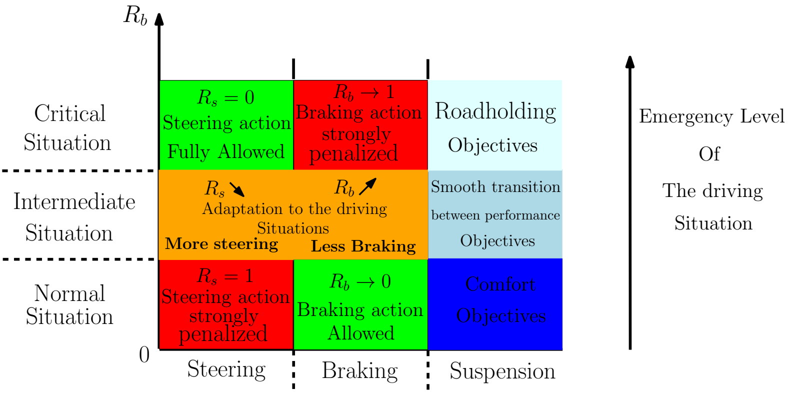
Control Issues through H_∞ formulation

- Lateral coordinated steering/braking control: parameter dependent weighting functions
- Full car vertical suspension control: fixed control structure for suspension force distribution, parameter dependent weighting functions (comfort vs safety)

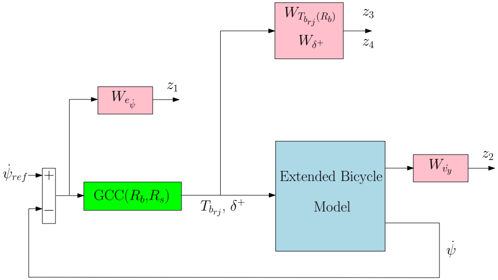
Actuators monitoring and scheduling strategy

Monitoring Parameters : to handle actuator malfunctions and activation.

- Braking efficiency R_b : torque transmission
- Steering activation R_s during emergency situation (low slip)
- LTR: roll induced load transfer by damper malfunctions



H_∞ coordinated steering/braking control



Vehicle model : Single track model (dry road).
Inputs/Ouputs:

$$
\begin{aligned}
w(t) &= [\dot\psi_{ref}(v)(t), M_{dz}(t)] \\
u(t) &= [\delta^+(t), T^+_{b_{rl}}(t), T^+_{b_{rr}}(t)] \\
y(t) &= e_{\dot\psi}(t) \\
z(t) &= [z_1(t), z_2(t), z_3(t)]
\end{aligned}
$$

Weighting functions for performance requirements

$W_{e_{\dot\psi}}$ and $W_{\dot v_y}$ are 1st order systems.

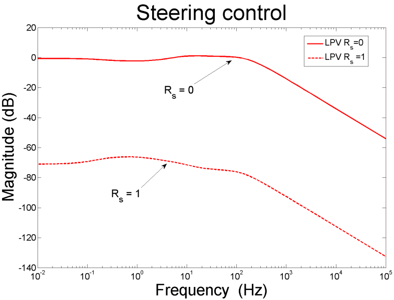
Weighting functions for actuator coordination

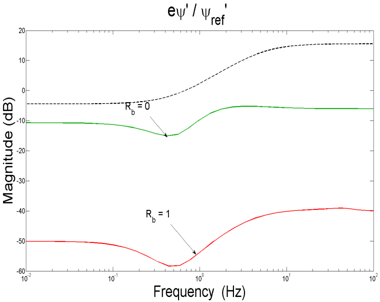
- $W_{\delta+}(R_s)$ = $R_s\times$ 1st order
- $W_{T_{b_{rj}}}(R_b)$ = $R_b\times$ 1st order

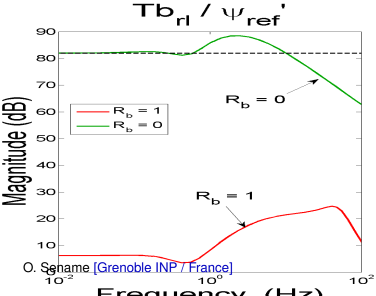
The variable gains allow to limit and activate or not the braking and steering actions

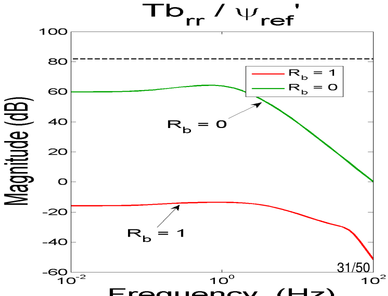
When a high slip ratio is detected (critical situation) , the tire may lock, so $R_b\to 1$ and the gain of the weighting function is set to be high.
This allows to release the braking action leading to a natural stabilisation of the slip dynamic.

Frequency-domain analysis

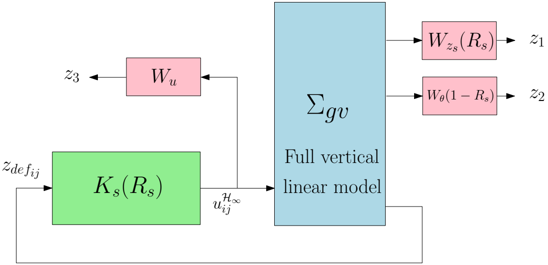


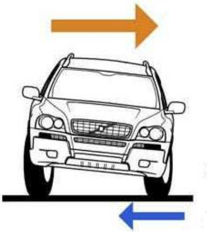


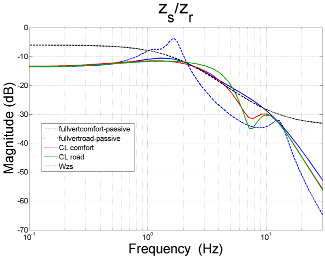


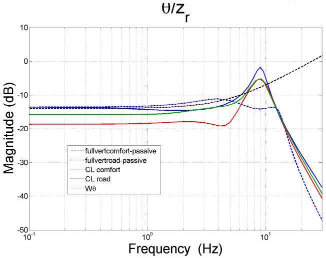


H_∞ suspension control configuration





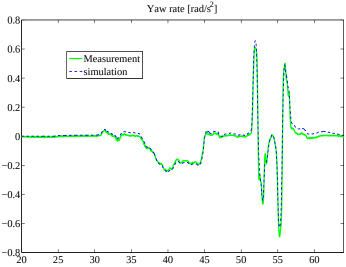




Validation: LPV control vs professional driver

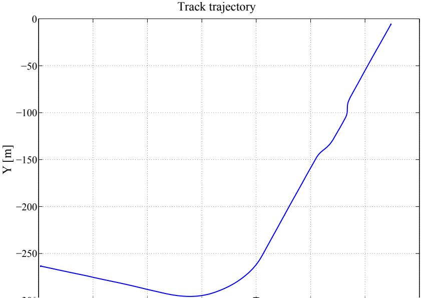
Vehicle Automotive 'GIPSA-lab' toolbox

- Full nonlinear vehicle model
- Validated in a real car "Renault Mégane" Special thanks to MIPS laboratory, Mulhouse, France (Prof. M. Basset):]
  see C. Poussot-Vassal PhD. thesis

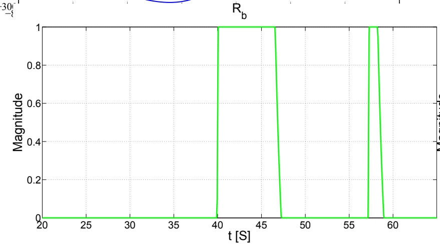


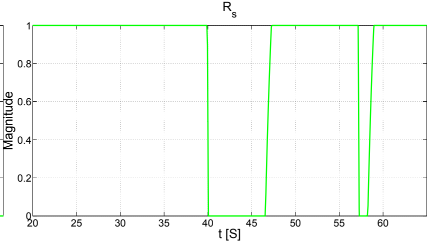
- The stabilizing torques T_b^* provided by the controller is then handled by a local ABS strategy Tanelli et al. (2008)

Scenarion and scheduling parameters

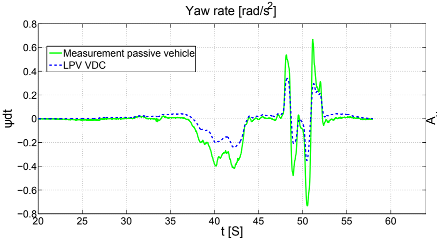


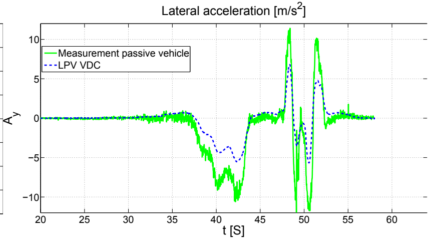
Experimental Moose performed by a professional driver on the Renault Mégane at $90km.h^{-1}$ (to assess the efficiency for obstacles avoidance). The circuit includes a left bend and then an obstacle avoidance in emergency situations to determine how well a vehicle evades a suddenly appearing obstacle.

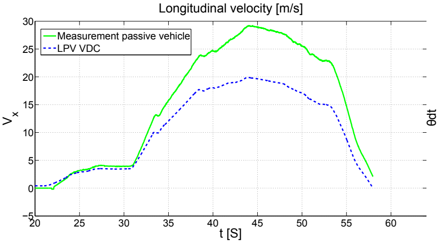


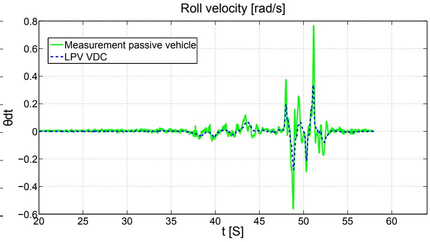


Vehicle dynamical variables

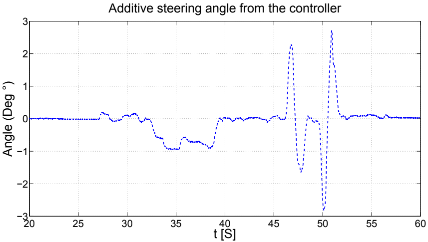








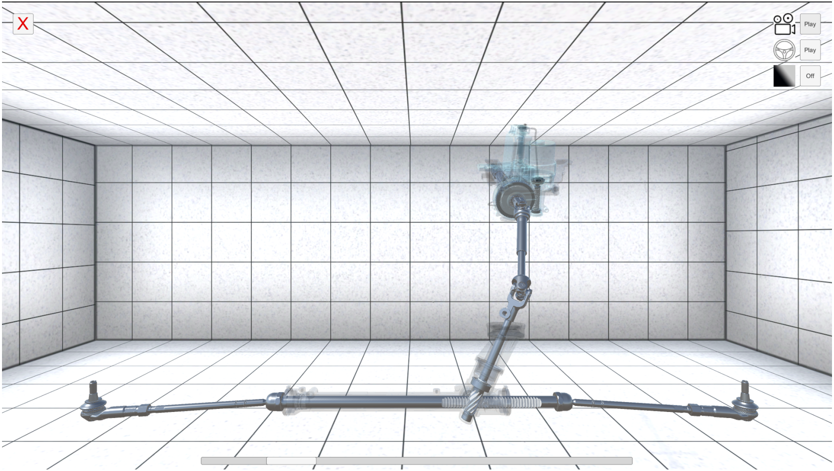
Steering control input



1. Improved vehicle dynamical behavior subject to critical driving situations
2. Coordinated and hierarchical use of three types of actuators, depending on the driving situations
3. LPV vs LTI: limitation of the braking actuation in critical situations to avoid wheel locking and skidding, and its coordination with active steering and semi-active suspension controllers, leading to vehicle stability and road handling improvements.
4. Convincing simulation results, obtained from experimental input data and performed with a validated complex nonlinear vehicle model

Outline

Electric Power Steering Systems JTEKT JTEKT CORPORATION - *K. Yamamoto*



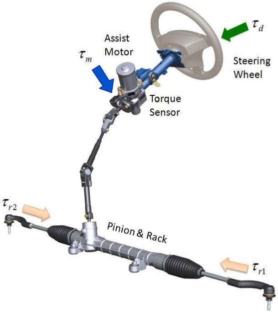
Assist mechanism within steering column (inside the cabin)

Recommended for compact vehicles with small rack force (< 10 kN)

C-EPS system model

System inputs

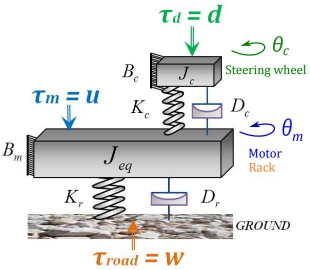
- Driver torque $\tau_d =: d$
- Motor assist torque $\tau_m := u$
- Rack force $F_r := w$



C-EPS system model

System inputs

- Driver torque $\tau_d =: d$
- Motor assist torque $\tau_m := u$
- Rack force $F_r := w$



Newton's second law of motion and neglecting dry frictions [El-Shaer2008,Marouf2013]

$$
\begin{aligned}
J_c\ddot{\theta}_c &= \tau_d - D_c\left(\dot{\theta}_c - \frac{\dot{\theta}_m}{R_m}\right) - K_c\left(\theta_c - \frac{\theta_m}{R_m}\right) - B_c\dot{\theta}_c \\
J_{eq}\ddot{\theta}_m &= \tau_m + \frac{D_c}{R_m}\left(\dot{\theta}_c - \frac{\dot{\theta}_m}{R_m}\right) + \frac{K_c}{R_m}\left(\theta_c - \frac{\theta_m}{R_m}\right) - B_m\dot{\theta}_m - K_r\frac{R_p^2}{R_m^2}\theta_m - D_r\frac{R_p^2}{R_m^2}\dot{\theta}_m - \frac{\tau_r}{R_m}
\end{aligned}
$$

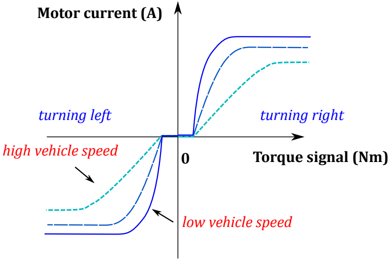
C-EPS state-space representation

$$
\left\{
\begin{aligned}
\dot{x} &= Ax + Bu + Ed + Ww \\
y &= Cx + Nn
\end{aligned}
\right.
$$

EPS Control Objectives

EPS requirements

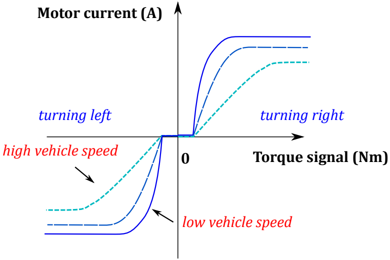
- Provide a suitable assistance torque
  ⇒ parking requires maximum assistance
- Ensure an adapted road-feedback
  ⇒ ↗ vehicle speed leads to ↘ assistance torque



EPS Control Objectives

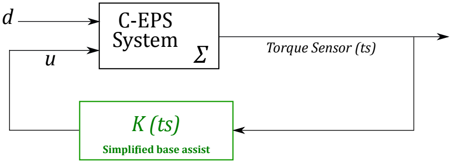
EPS requirements

- Provide a suitable assistance torque
  ⇒ parking requires maximum assistance
- Ensure an adapted road-feedback
  ⇒ ↗ vehicle speed leads to ↘ assistance torque



- Guarantee closed-loop stability
- Be robust to model uncertainties
- Have low complexity regarding implementation issue

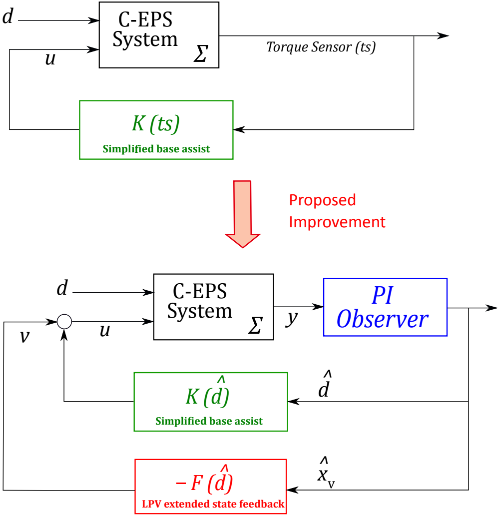
Proposed LPV Control Structure



Existing strategy

- Base assist only: not sufficient for optimal performances
- Require a torque sensor
- empirical approach: needs an ad-hoc fine tuning using on-board experimental tests

Proposed LPV Control Structure



Existing strategy

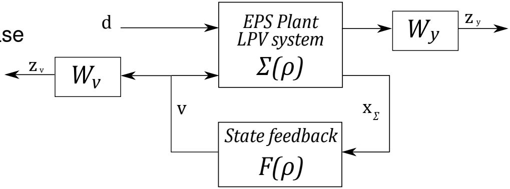
- Base assist only: not sufficient for optimal performances
- Require a torque sensor
- empirical approach: needs an ad-hoc fine tuning using on-board experimental tests

Proposed strategy

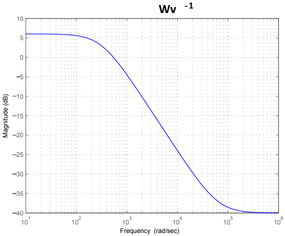
- ensures global stability (safety) and performance
- does not need any torque sensor (reduce the EPS production costs + safety)
- model-based control strategy

LPV EPS extended state-feedback controller

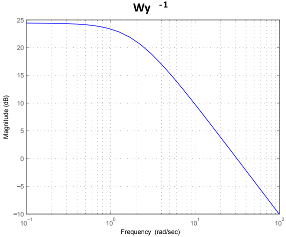
LPV system: C-EPS system + Base assist $K(\rho)$, steering torque dependent $\rho = \hat{d}$



Weighting function on actuator constraint

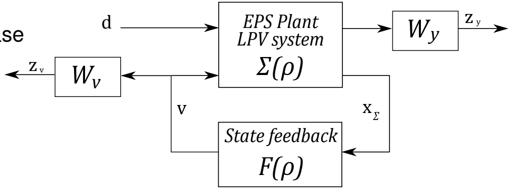


Weighting function on performance



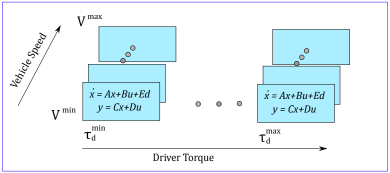
LPV EPS extended state-feedback controller

LPV system: C-EPS system + Base assist $K(\rho)$, steering torque dependent $\rho = \hat{d}$



LPV parameter-dependent state-feedback [Wu1995]

Gridding approach w.r.t the steering torque



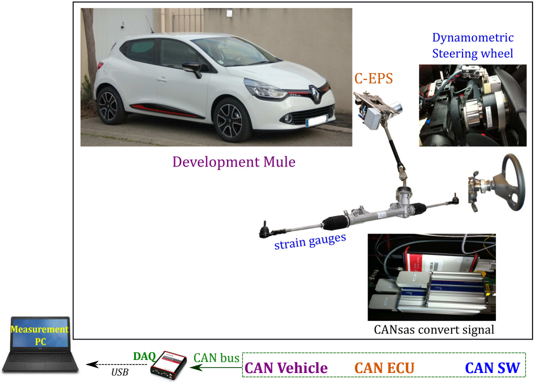
Parameter dependent Lyapunov function and control gain

To solve the LMIs, a basis is chosen to express the matrix $P(\rho)$ and $Y(\rho)$.

$$\begin{aligned} P(\rho) &= P_0 + \rho P_1 + \rho^2 P_2 \\ Y(\rho) &= Y_0 + \rho Y_1 + \rho^2 Y_2 \end{aligned}$$

Parameter dependent state feedback $F(\rho) = -Y(\rho)P(\rho)^{-1}$: obtained computing the LMIs over the gridded points using YALMIP interface and SeDuMi solver.

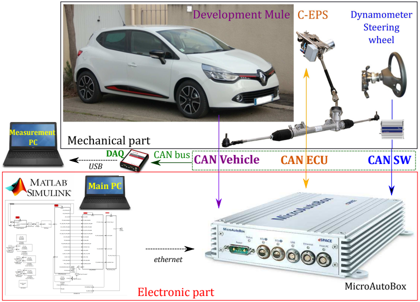
Vehicle configuration: Clio IV



On board set-up, specific devices

- Mechanics: C-EPS prototype (low pinion/rack ratio)
- Data acquisition: motor current, driver torque (dynamometric steering wheel), rack force (instrumented tie-rods) with CANsas modules to convert signals
- Implementation: Quick Prototyping, Simulink model implemented on MicroAutoBox

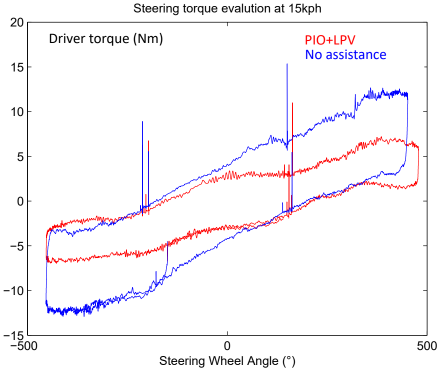
Strategy Implementation

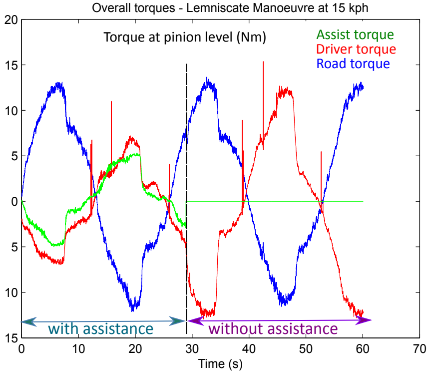


Operating configuration

- $\mathcal{H}_\infty/\mathcal{H}_2$ PI Observer + LPV state-feedback controller
- Used measurements signals: steering wheel angle θ_c, motor angle θ_m
- Tests: Lemniscate, Sinusoidal manoeuvre

Test 1 - Lemniscate at 15 km/h





Quantitative performance analysis

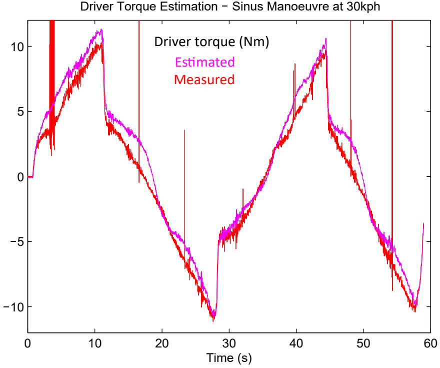
- No assistance $\rightarrow \tau_d^{max} = 12.90Nm$
- PIO+LPV $\rightarrow \tau_d^{max} = 6.95Nm$

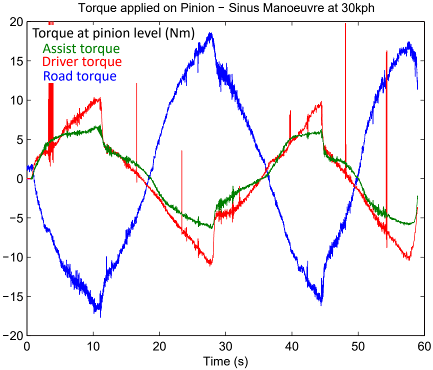
On-center level almost $4Nm$

$\tau_d^{max} < 7Nm$
$\tau_m^{max} < 6Nm$
$\tau_{road}^{max} < 13Nm$

Good assist level reducing the steering effort by half

Test 2 - Sinus at 30 km/h





Quantitative error analysis

- RMSE = 1.2736 Nm
- NRMSE = 5.75%

Good estimation results in real-time

$\tau_d^{max} < 10Nm$
$\tau_m^{max} < 7Nm$
$\tau_{road}^{max} < 17Nm$
Good assist level to be improved
Consistent feeling $\nearrow \tau_d$ with $\nearrow V_{spd}$

Outline

Conclusions

Many interests of the LPV approach

+ Modelling of complex systems (but still less than nonlinear formulation)
+ Control design with varying performances, ensuring internal stability and robust-like performances
+ Observer/Filter design... for Fault Detection and Isolation
+ A tool to design adaptive FTCS
+ Can be extended to mixed-objectives problems (e.g $\mathcal{H}_\infty$, $\mathcal{H}_2$...) through LMI (and/or nonsmooth) tools
+ Can be applied to any type of applications:
  - Mechanics, Mechatronics, Robotics
  - Energy, Power & Hydraulic plants
  - Consumer electronics
  - ...

Grenoble's studies on LPV systems and approaches

Former PhD students on LPV approaches

A. Zin, D. Robert, C. Gauthier, C. Briat, C. Poussot-Vassal, S. Aubouet, E. Roche, D. Hernandez, J. Lozoya, A-L Do, M. Rivas, S. Fergani, J-C Tudon, N. Nwesaty, M-Q Nguyen, D. Hernandez, K. Yamamoto, V-T Vu, D. Dubuc, T-P Pham , M. Menezes

Complex systems

- Non linear models
- Account for various operating conditions using a variable "equilibrium point":
- LPV Time-Delay Systems

Integration with Fault Diagnosis

LPV Adaptive Fault-scheduling Tolerant Control

LPV control = adaptation

- Real-time performance adaptation using parameter dependent weighting functions
- Control under computation constraints: variable sampling rate controller
- Control allocation of MIMO systems through a parameter for the control activation (of each actuator)

Applications

Engine, Vehicle Dynamics, Electric Power Steering, Autonomous Underwater Vehicle, Fuel Cell, Electrical vehicle RENAULT Passion for life JTEKT JTEKT CORPORATION DELPHI VOLVO TRUCKS

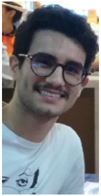
Warm thanks to ...

Juan-Carlos Tudon

Charles Poussot

Soheib Fergani

Manh Quan Nguyen



Marcelo Menezes

et bien sûr à mon collègue Dr. Luc Dugard

Merci pour votre attention