DVS®: a new technology for substituting real sensors with Virtual Sensors

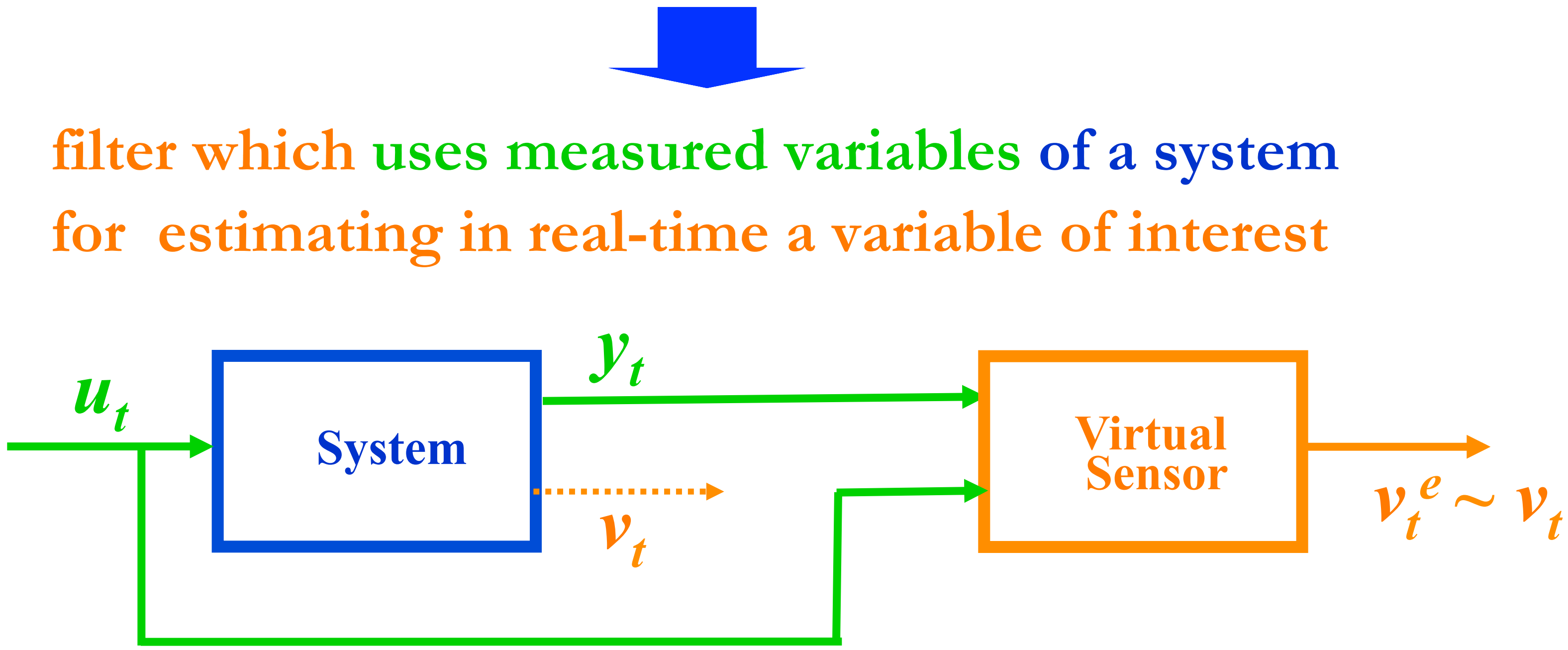
Mario Milanese, Modelway srl

Vehicle Dynamics Expo

Stuttgart, June 12, 2012

Virtual Sensor

filter which uses measured variables of a system for estimating in real-time a variable of interest

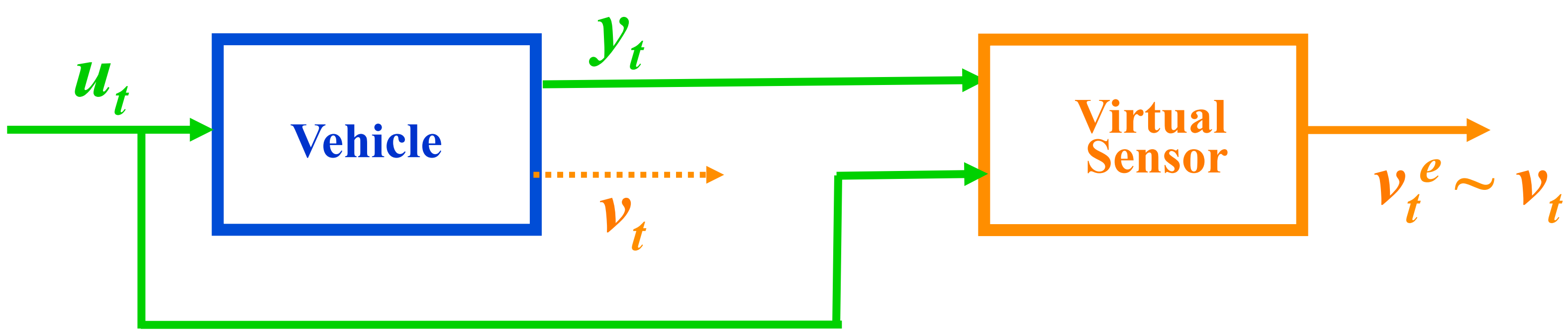


Virtual sensors can be realized as:

- Software code implemented on electronic board
- Embedded system (FPGA,….)

Vehicle lateral dynamics examples

- **VS for the estimation of variables relevant for stability control systems (ESP,VDC,…)**



- **Yaw-rate VS:**

u_t= *steering angle*

y_t= *lat acc; long speed*

v_t= *yaw rate*

- **Side-slip angle VS:**

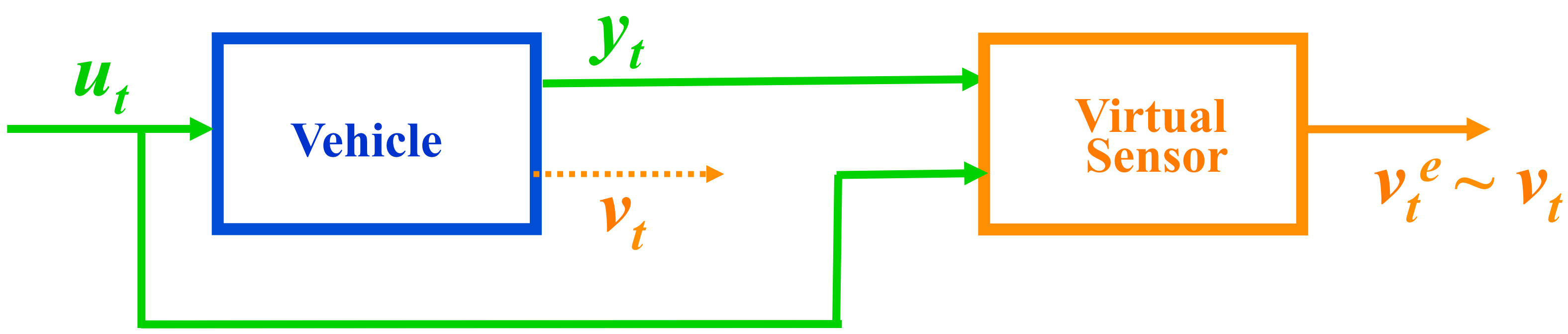
u_t= *steering angle;*

y_t= *lat acc; long speed; yaw rate*

v_t= *side-slip angle*

Vehicle vertical dynamics examples

- VS for the estimation of variables relevant for semi-active suspension systems (Sky-Hook, FMPC,…)



- **Diff-speed VS1:**

u_t= damping force

y_t= sprung mass acc; unsprung mass acc

v_t= diff-speed of sprung and unsprung masses

- **Diff-speed VS2:**

u_t= damping force

y_t= sprung mass acc

v_t= diff-speed of sprung and unsprung masses

MODELWAY INTELLIGENCE TECHNOLOGY

Virtual Sensor design

- In the literature, a large number of methods (Kalman filter, particle filter, H_∞ filter, MH filter,…) have been proposed for the design of filters giving 'small' estimation error $v_t - v_t^e$
- However, all these methods assume that the system equations relating the variables u_t, y_t and v_t are exactly known
- In real applications the system is not exactly known and VS design is performed in two steps:
  1. A model, describing the equations relating the variables u_t, y_t and v_t, is constructed, typically making use also of experimental data
  2. One of the existing filtering method is applied, using the identified model as system description

Drawbacks of two-step VS design

- The VS is designed for the identified model, which is an approximation of the real system. Evaluating how model approximation affects the filter accuracy is an open problem, even for linear systems
- Designing optimal filters for nonlinear systems is hard and only approximate filtering methods are available (e.g. Extended Kalman Filter, derived by sequential linearization along system trajectory)
- Due to the above problems (approximation in modeling and filtering), no method exist for evaluating how far from optimality the two-step VS design may be. Even the boundedness of estimation error is not easily achieved for complex systems

Direct VS design

- A new VS design methods has been recently developed, able to overcome the drawbacks of previous VS design methods
- The method, called DVS®, is based on direct filter design from experimental data

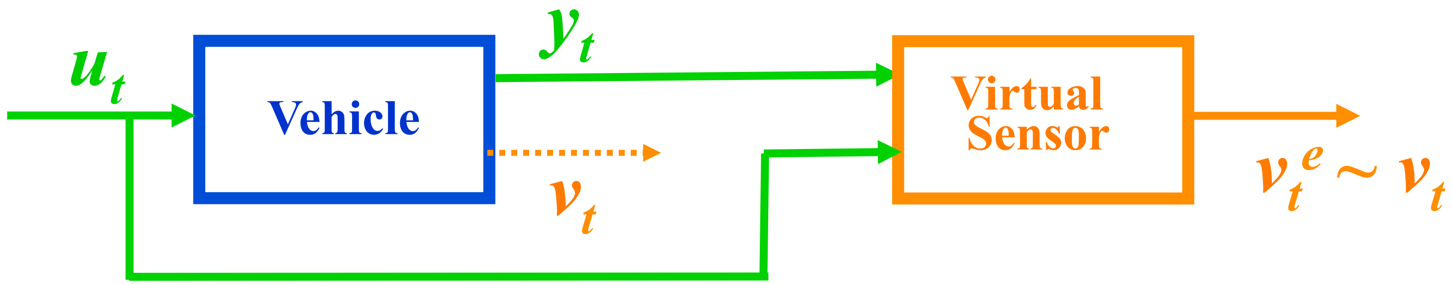
The experimental data are used for directly designing the VS without the need of identifying a model of the actual system

- *M. Milanese, et al., "The filter design from data (FD2) problem: Nonlinear Set Membership approach," Automatica, 2009.*
- *C. Novara, et al., "The filter design from data (FD2) problem: Parametric Statistical approach," Int. J. of Robust and Nonlinear Control, 2011*

Features of DVS design

- At difference from the other existing VS design methods, optimal DVS can be actually designed for LTI, LPV and NL systems
- Thus, DVS design gives estimation errors lower or equal than the ones of any other VS design
- Equality holds ONLY IF the identified model is an exact representation of the real system
  AND an optimal filter can be actually derived.
  As above discussed, both conditions never hold in real applications
- In real applications, DVS design tipically achieves significantly lower errors than existing VS design methods

Experimental results: Yaw-rate VS



- u_t= *steering angle;* y_t= *lat acc; long speed;* v_t= *yaw rate*
- These variables has been measured on a passanger car for different maneuvers (SAS: steering angle steps; DLC: double lane change; FS: frequency sweep)
- A first set of data has been used for the design of 3 VS:
  - EKF: Extended Kalman Filter
  - PF: Particle Filter
  - DVS: Direct Virtual Sensor

MODELWAY INTELLIGENCE TECHNOLOGY

Experimental results: Yaw-rate VS

- For EKF/PF VS's, the design data set is used for the identification of a lateral dynamics model. The corresponding VS's are obtained using Extended Kalman/Particle filtering of the identified model
- The DVS is directly computed using the design data, without requiring model identification
- The estimation errors of the 3 VS's is evaluated on a new data set not used for VS design:

$$RMSE = \sqrt{\sum_{1}^{N} (v_t - v_t^e)^2 / N} \qquad MAXE = \max_{t=1}^{N} | v_t - v_t^e |$$

Experimental results: Yaw-rate VS

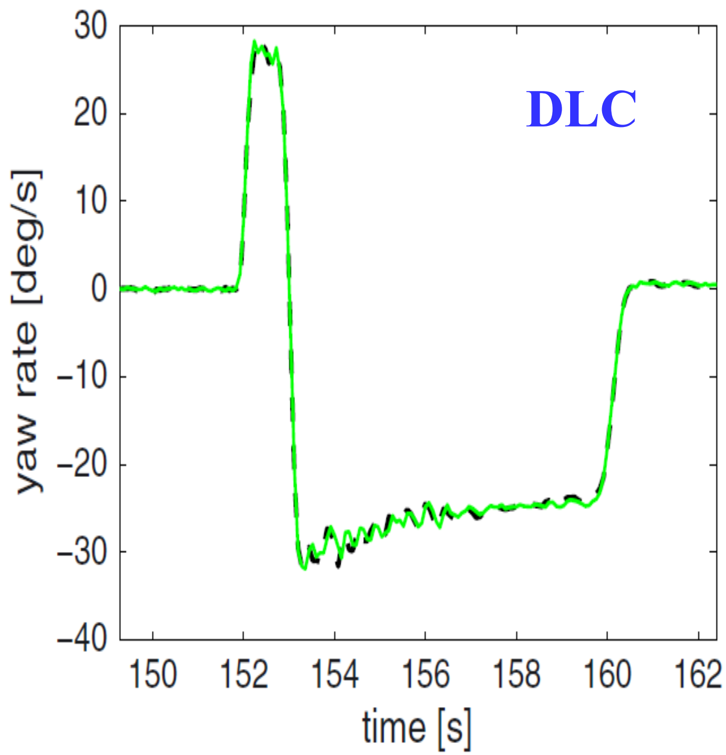
%RMSE

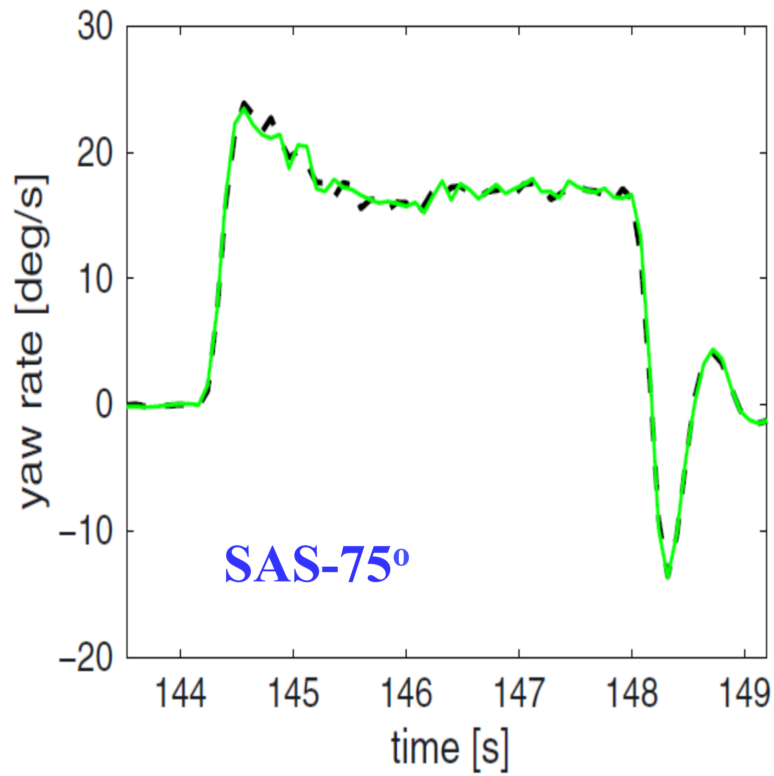
Maneuver	EKF	PF	DVS
SAS-50^o	7%	7%	4%
SAS-75^o	11%	13%	4%
DLC	7%	8%	3%
FS	8%	8%	4%

%MAXE

Maneuver	EKF	PF	DVS
SAS-50^o	11%	14%	8%
SAS-75^o	13%	22%	7%
DLC	15%	22%	7%
FS	13%	13%	7%

Experimental results: Yaw-rate VS



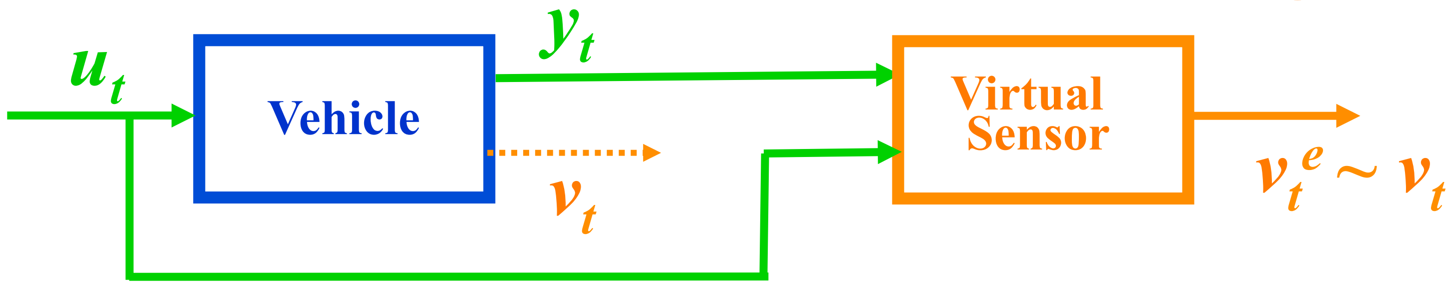


black: measured yaw rate

green: DVS yaw rate estimate

MODELWAY
INTELLIGENCE TECHNOLOGY

Experimental results: Side-slip angle DVS



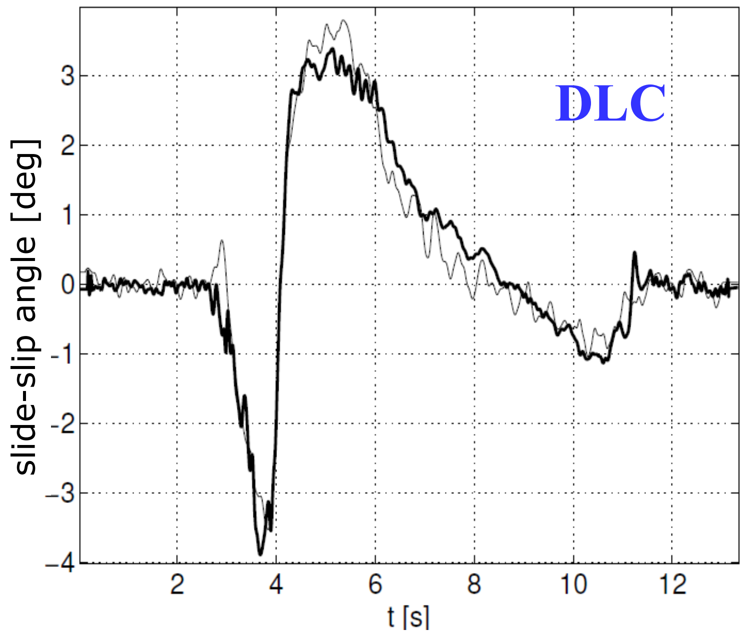
- *u_t= steering angle; y_t= lat acc; long speed; yaw rate*
  v_t= side-slip angle
- These variables has been measured on a passanger car for different maneuvers with side-slip angles up to 15 deg
- Side-slip angle has been measured by a Datron sensor
- A first set of data is used for the design of a DVS
- EKF/PF VS designs have been tested, but no acceptable results have been obtained

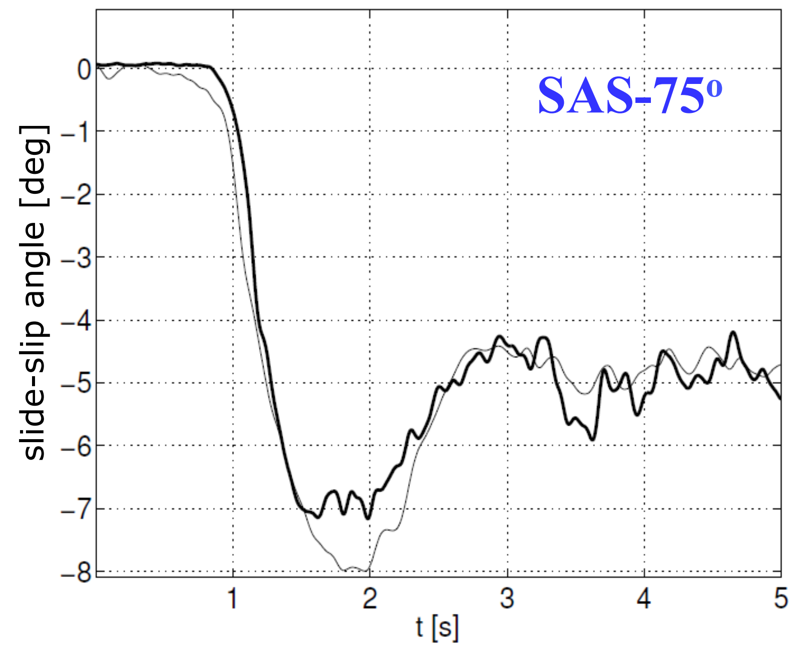
MODELWAY INTELLIGENCE TECHNOLOGY

Experimental results: Side-slip angle DVS

- **DVS error evaluated on a independent data set**

$$RMSE \leq 0.25 \deg$$
$$MAXE \leq 1.7 \deg$$





thin: measured slide-slip angle

thick: DVS slide-slip angle estimate

MODELWAY INTELLIGENCE TECHNOLOGY

Conclusions

- At difference from the other existing VS design methods, optimal DVS can be actually designed for LTI, LPV and NL systems
- Thus, DVS design gives estimation errors lower or equal than the ones of any other VS design
- Equality may hold only under conditions which rarely hold in real applications, where DVS design tipically achieves significantly lower errors than the existing VS design
- The overall workload for the DVS design is significantly lower than for the other methods, e.g. weeks instead of months for complex systems

References

Theory

Vehicle dynamic apps

- *M. Milanese, et al.,"The filter design from data (FD2) problem: Nonlinear Set Membership approach," Automatica, 2009*
- *C. Novara, et al., "The filter design from data (FD2) problem: Parametric Statistical approach," Int. J. Rob. Nonlinear Contr., 2011*
- *C. Novara, F. Ruiz, M. Milanese, "Direct identification of optimal sm-lpv filters and application to vehicle yaw rate estimation,", IEEE Trans. Control System Technology, 2011*
- *M. Milanese, D. Regruto, A. Fortina, "Experimental results in vehicle sideslip angle estimation" SAE Conference, Detroit, 2006*
- *P. Borodani, "Virtual sensors: an original approach for variables estimation in automotive control systems," AVEC Conf., Kobe, 2008*
- *M. Canale, et al., "A study on the use of virtual sensors in vehicle control," IEEE Conf. on Decision and Control, Cancun, 2008*
- *M. Milanese, et al., "Linear virtual sensors for vertical dynamics of vehicles with controlled suspensions," Eur. Contr. Conf., Kos, 2007*

MODELWAY INTELLIGENCE TECHNOLOGY

Thank you!

For more information on
DVS® technology:
mario.milanese@modelway.it

DVS® is a registered trademark of Modelway srl