Control paradigms are enriched with AI (and vice versa)

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Automatic control issues and solutions

Classical issues in automatic control

1. identification
2. simulation
3. observation
4. control and performance

for dynamical systems, in presence of uncertainties, heterogeneities, constraints...

Proposed solutions

1. reduced-order modeling
2. performance certifications
3. observation and control *could be* done separately
4. cascade, feedback and series are possible

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AI

Opportunities

1. scientific computation
2. big data, sensors are everywhere
3. optimization and efficient algorithms
4. recording of long time-scale signals is possible

Proposed solutions

1. large neural networks
2. efficient applications
3. automatic learning and processing

Already many successes that were not possible 3 years ago.

An example of great success

Matchmaking between AI and sismology

Recent work of Michel Campillo to detect seismic signals [Seydoux et al., *Nature Com.*; 2020]:

- uses [Agen, Mallat; 2014] wavelet on 10^{10} samples on a year for one station
- scattering network to compute clusters
- Human Intelligence is needed but Artificial Intelligence helps
- work in progress in sismology: 800 stations in Alps, on decades.

Matchmaking of Automatic Control and AI?
In both directions?

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Outline

Automatic Control and AI

AI succeeds to improve control paradigms on various issues:

1. reduced-order modelling and simulation

   ➪ two approaches illustrated in fluid mechanics

2. identification and observation

   ➪ illustrated on navigation problem

and vice versa:

3. systems theory for AI

   ➪ a few references only

✗ Non-exhaustive and only personnal presentation on a fastly growing subject

✓ Presentation will be updated and all comments are welcome

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1 – Scientific machine learning opportunities

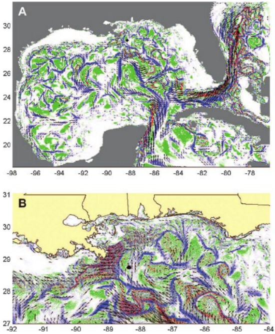
For many physical problems, models are very complex, continuous, varying over the space domain

Big-data alone in not enough, we need

- predictibility
- domain knowledge
- interpretability

Physical models are

- multiscale multiphysics phenomena
- infinite-dimensional dynamics, large-scale models with nonlinearities ...
- computationally very expensive



Gulf of Mexico

Computational science approach:

- solve complex dynamical systems (as partial differential equations (PDEs) or nonlinear systems)

$$\begin{aligned} \dot{x} &= f(x) \\ y &= h(x) \end{aligned}$$

to get training data

- fix the structure:

$$\begin{aligned} \dot{\hat{x}} &= A\hat{x} \\ y &= C\hat{x} \end{aligned}$$

- find the best $\hat{A}$, $\hat{B}$ and $\hat{C}$, by solving a convex problem as

$$\min_{A,B,C} \quad \sup_{trajectories\ \hat{x},\ data\ x} \quad \|h(x) - C\hat{x}\|$$

How to do that?

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How to do that?

Computational science approach:

- solve complex dynamical systems (as partial differential equations (PDEs) or nonlinear systems)

$$\begin{aligned} \dot{x} &= f(x) \\ y &= h(x) \end{aligned}$$

  to get training data

- fix the structure:

$$\begin{aligned} \dot{\hat{x}} &= A\hat{x} + Bu \\ y &= C\hat{x} \end{aligned}$$

- find the best $\hat{A}$, $\hat{B}$ and $\hat{C}$, by solving a convex problem as

$$\min_{A,B,C} \quad \sup_{\textit{trajectories } \hat{x},\ \textit{data } x} \|h(x) - C\hat{x}\|$$

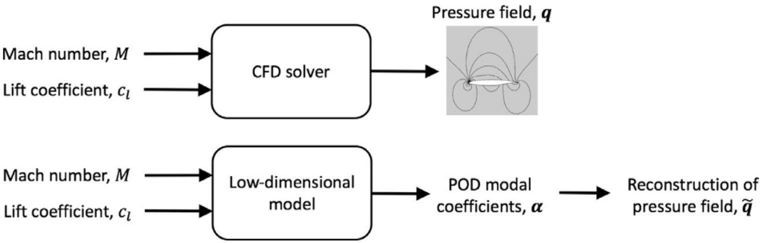
How to do that?

First approach: aerodynamic example

See [K. Willcox et al., Projection-based model reduction: Formulations for physics-based machine learning; 2019]:

- Euler Equation for the inviscid steady flow over an airfoil
- project the PDE model, and solve an optimization problem
- large Mach number range and different lift coefficient are considered

for a prediction purpose and reduced-order modelling



See also Charles Poussot-Vassal (ONERA)

Second approach: Koopman operator

Consider the Koopman operator and flows along the nonlinear ODE/PDE models.

Koopman operator is a linear operator ✓
on a infinite dimensional system ✗

[A. Mauroy and I. Mezic, Global stability analysis using the eigenfunctions of the Koopman operator]:
Its spectrum is related to stability properties

Prediction problem

[M. Korda and I. Mezic, *IEEE-TAC*, to appear] succeeds to

- compute the eigenfunctions Ψ
- find the best C, that is:

$$\min_{C} \sup_{trajectories\ x} \|h(x) - C\Psi(x)\|$$

The prediction of $h(x(t))$ is given by the output of

$$\begin{aligned} \dot{\hat{x}} &= A\hat{x} \\ \hat{x}_0 &= h(x_0) \\ y &= C\hat{x} \end{aligned}$$

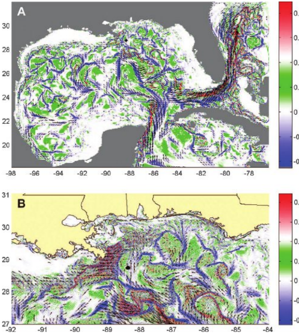
Efficient algorithm
and proof of the approximation of any output by such eigenfunctions.

Learning from data, and algorithm exploiting complex models

Real example on fluid dynamics

Estimation and simulation using real data in Gulf of Mexico after the Deepwater Horizon disaster

[I. Mezic, et al. A new mixing diagnostic and gulf oil spill movement. *Science*; 2010.]



Gulf of Mexico

The controlled case could be considered as well, but rather many academic examples so far
[M. Korda, I. Mezic. Optimal construction of Koopman eigenfunctions for prediction and control]

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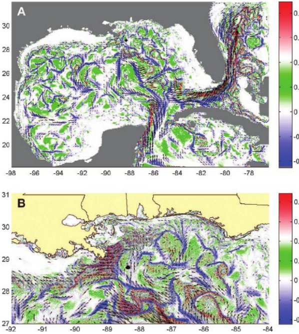

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2 – For identification and observation problems

Again data-based observation should be avoided
But rather AI needs to be coupled with physical models and classical observation techiques

One example in navigation and object tracking problems:

- identification and calibration of unknown parameters
- observation using noisy and biaised measurements

⇨ by coupling of Machine Learning with Kalman Filter.

Given one (or several) gyroscope, accelerometer and magnetometer

How to observe the position, the orientation and the magnetic heading of the body?

Industrial developement with Sysnav

The continuous-time dynamic model is nonlinear, time-varying in non-Euclidian space:

$$
\begin{array}{rcll}
\frac{dq}{dt} & = & \frac{1}{2}[\omega\times]q & \text{quaternion} \\
\frac{dv_b}{dt} & = & -\omega \times v_b + a_b - Rg & \text{speed} \\
\frac{dM_n}{dt} & = & R^\top v_b & \text{position} \\
\frac{dB_b}{dt} & = & -\omega \times B_b + \nabla B_b v_b & \text{magnetic field}
\end{array}
$$

in the body frame

Calibration problem

Magnetometer:

$$y_b^i = \alpha_b^i B_b^i + \beta^i \qquad i = x, y, z$$

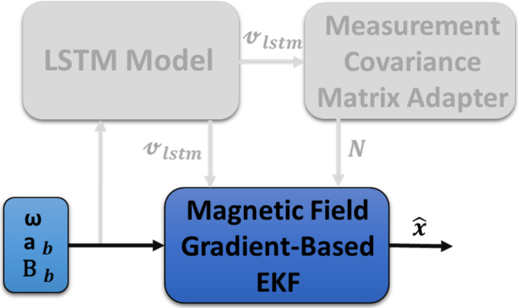
where α^i and β^i are not very well known or slowly varying
Needs to be calibrated

Optimization algorithm has been used to find the best α_b^i and β_b^i

To do that we used the physical model of magnetometer and motion capture measures
See [Chesneau, et al.; 2019]

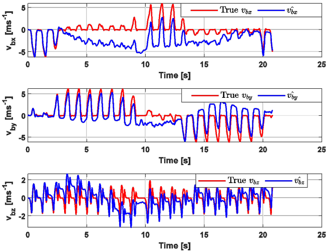
Observation problem

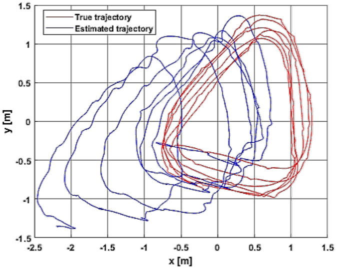
The previous model is nonlinear and may be non-observable (depending on the to-be-observed trajectory)
Let us compute an Extended Kalman Filter



Using an EKF only

Using and EKF and checking the position with a motion capture system



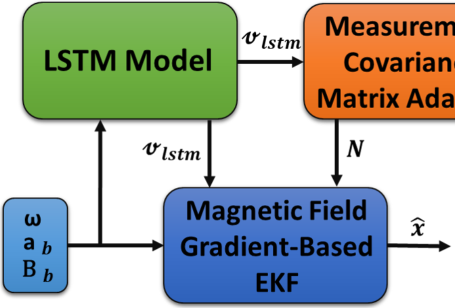


True speed Estimated speed

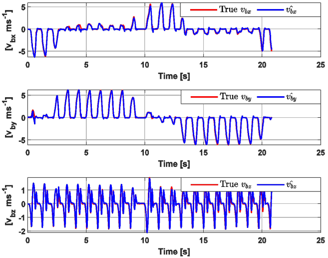
True position Estimated position

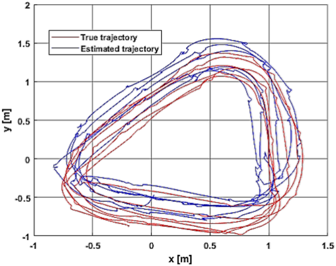
EKF and LSTM

Learning from several training trajectories with motion capture data using a Long Short-Term Memory (LSTM) approach
And adding the LSTM output as an input of the Kalman Filter



Combining an EKF with a LSTM





True speed Estimated speed

True position Estimated position

See Makia Zmitri and the joint work with Sysnav

3 – Control techniques for AI?

System theory is very useful for estimating the
Uncertain quantification and uncertainty propagation

There is already a very large literature developping control techniques for AI

- Use of statistical model
- Use of robust control design

Still a lot of things to be done.

Some references on that

• Use of statistical techniques for uncertainty propagation.
Sensitivity analysis
See the book [S. D. Veiga, F. Gamboa, et al.; 2020]

• Use linear optimal control problems to understand performance of Reinforcement Learning techniques
See [P. Seiler et al., Recovering Robustness in Model-Free Reinforcement Learning; 2019] and ONERA (Biannic, Loquen...)

• Large literature on nonlinear control systems, in particular with isolated nonlinearities [Tarbouriech et al.; 2011].
Such elements could be used in AI to prove properties of neural networks
[L. Grigoryeva and J.-P. Ortega; 2018], [H. Jaeger; 2001]
to cite just a few

Still need your attention!

Conclusion

How AI and scientific computation could be useful
for control objectives:

- reduced-order modelling and simulation
- identification
- observation
- (and control)

And vice versa
RL and AI could be better understood and useful
using systems theory:

- statistical estimators and sensitivity analysis
- robust control
- nonlinear controlled

Matchmaking of Automatic Control and AI

support from the Chair on *AI and Automatic Control* and