

International Workshop on Stochastic Weather Generators

Reduced flow models from a stochastic Navier-Stokes theorem

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17 septembre 2014

PLAN

INTRODUCTION

STOCHASTIC FLUID DYNAMIC MODEL

REDUCED MODEL

RESULTS

CONCLUSION

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INTRODUCTION

Why using stochastic fluid dynamic ?

Why a reduced model ?

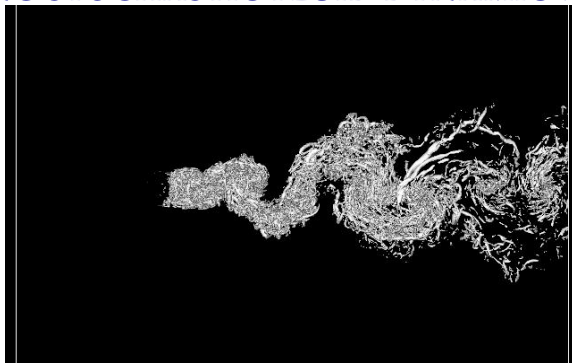
STOCHASTIC FLUID DYNAMIC MODEL

REDUCED MODEL

RESULTS

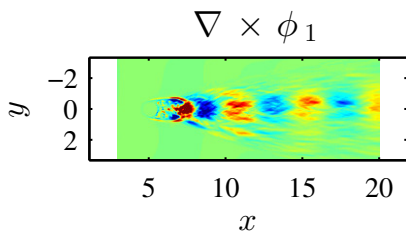
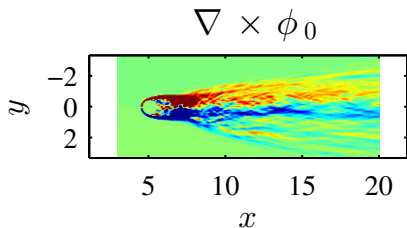
CONCLUSION

WHY USING STOCHASTIC FLUID DYNAMIC ?

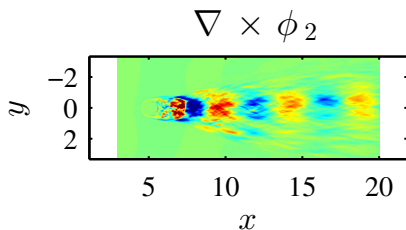


- ▶ Usual advantages of stochastic methods
- ▶ Fluid dynamics, and especially geophysical fluid dynamics, is too complex to be solved at all scales
- ▶ Chaotic system
- ▶ Non-unique solution

WHY A REDUCED MODEL ?



- ▶ Simplified simulations
- ▶ Decomposition of the physic



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INTRODUCTION

STOCHASTIC FLUID DYNAMIC MODEL

Classical Large Eddy approach

Stochastic Reynolds-transport theorem

Mass continuity

Stochastic Navier-Stokes model

REDUCED MODEL

RESULTS

CONCLUSION

CLASSICAL LARGE EDDY APPROACH

Numericians approach :

$$\frac{\partial \bar{T}}{\partial t} + \nabla \cdot (\bar{T}\bar{u}) = \nabla \cdot (-\overline{u'T'})$$

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CLASSICAL LARGE EDDY APPROACH

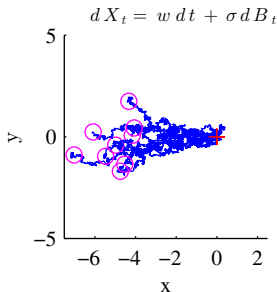
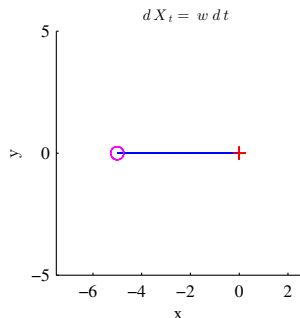
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STOCHASTIC REPRESENTATION OF THE REYNOLDS-TRANSPORT THEOREM

Notations :

- ▶ $dX_t = w(X_t, t)dt + \sigma(X_t, t)dB_t$
- ▶ B_t an \mathbb{I}_d -cylindrical Wiener process (Da Prato & Zabczyk (1992))
- ▶ $\sigma(\cdot, t)$ an Hilbert-Schmidt operator on $(L^2(\mathbb{R}^d))^d$ defined by its kernel $\check{\sigma}(\cdot, \cdot, t)$

Thus,

$$\sigma(x, t)dB_t \sim \mathbf{GP}(0, \delta(t - t')\sigma(x, t)\sigma^t(x', t)dt)$$

- ▶ Local covariance matrix

$$a(x, t) \triangleq \sigma(x, t)\sigma^t(x, t) = \int_{\Omega} \check{\sigma}(x, z, t)\check{\sigma}^t(x, z, t)dz$$

STOCHASTIC REPRESENTATION OF THE REYNOLDS-TRANSPORT THEOREM

Theorem

$V(t)$ being a material element,

$$d_t \int_{V(t)} q dx = \int_{V(t)} \left(d_t q + \nabla \cdot \left(q dX_t + q \sigma (\nabla \cdot \sigma)^t dt - \frac{1}{2} \nabla \cdot (aq)^t dt \right) \right) dx$$

Proof : Mémin (2014)

MASS CONTINUITY

$$\begin{aligned} d_t \int_{V(t)} \rho dx &= d_t m(t) \\ &= 0 \end{aligned}$$

Thus,

Theorem

$$0 = d_t \rho + \nabla \cdot \left(\rho dX_t + \rho \sigma (\nabla \cdot \sigma)^t dt - \frac{1}{2} \nabla \cdot (a \rho)^t dt \right)$$

Application : Mean field

$$\frac{\partial \mathbb{E}(\rho)}{\partial t} + \nabla \cdot (\mathbb{E}(\rho) w^*) = \nabla \cdot \left(\frac{1}{2} a \nabla \mathbb{E}(\rho) \right)$$

with

$$w^* = w + \sigma (\nabla \cdot \sigma)^t - \frac{1}{2} (\nabla \cdot a)^t$$

STOCHASTIC NAVIER-STOKES MODEL

Theorem

If w has finite variations and $\int_0^t p dt'$ is replaced by $\int_0^t p' dt' + d\hat{p}$ then

$$\rho \left(\frac{\partial w}{\partial t} + (w \cdot \nabla) w \right) = \boldsymbol{\tau}(w) + \rho g - \nabla p' + f_V(w)$$

$$\rho(\sigma dBt \cdot \nabla) w = -\nabla d\hat{p} + f_V(\sigma) dBt$$

where

$$\left\{ \begin{array}{l} \forall k, \tau_k(w) = \frac{1}{2} \left(\nabla \cdot (\nabla \cdot (\rho a w_k))^t - \nabla \cdot (\nabla \cdot (\rho a))^t w_k \right. \\ \quad \left. - \rho ((\nabla \cdot \sigma) \sigma^t \nabla) w_k \right. \\ \left. f_V(g) = \mu \left(\nabla^2 g + \frac{1}{3} \nabla (\nabla \cdot g) \right) \right.$$

Proof : Mémin (2014)

STOCHASTIC NAVIER-STOKES MODEL

Applications :

- ▶ Large eddies simulation
- ▶ Uncertainty quantification
- ▶ Filtering
- ▶ Mixing diagnostics

...

PLAN

INTRODUCTION

STOCHASTIC FLUID DYNAMIC MODEL

REDUCED MODEL

Principle

Proper Orthogonal Decomposition

Classical approaches

Our approach

Estimation of a

RESULTS

CONCLUSION

PRINCIPLE

- ▶ Using both a model and data (N snapshots).
- ▶ Galerkin projection :

$$u(., t) \in \mathbf{Span}(\phi_0, \dots, \phi_n)$$

- ▶ Coefficients of the decomposition, b_i , are time-dependent.
- ▶ $\frac{\partial u}{\partial t} = I + L(u) + C(u, u)$ (a PDE) becomes :

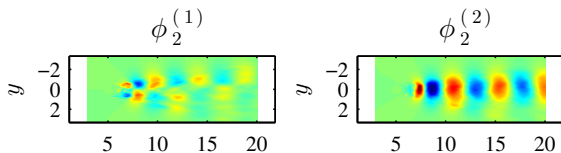
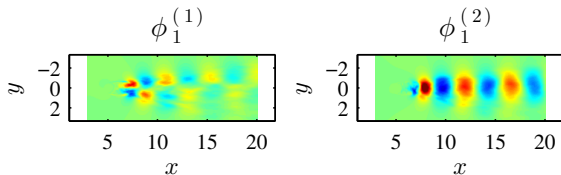
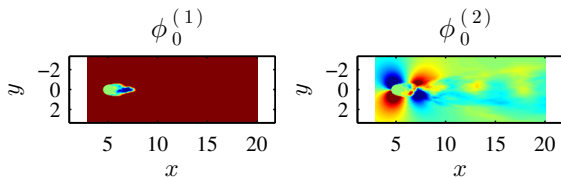
$$\forall i, \frac{db_i}{dt} = \left(\int_{\Omega} \phi_i \cdot I \right) + \sum_{p=0}^n \left(\int_{\Omega} \phi_i \cdot L(\phi_p) \right) b_p + \sum_{p,q=0}^n \left(\int_{\Omega} \phi_i \cdot C(\phi_p, \phi_q) \right) b_p b_q \quad (\text{ODEs})$$

PROPER ORTHOGONAL DECOMPOSITION

- ▶ Analogue to PCA apply to $(u(., t_1), \dots, u(., t_N))$:
 Analogue of variables : Values on points of the space
 Analogue of realizations : Snapshots
- ▶ Modes $\phi_i(x)$ are sorted regarding an energetic criterion

$$u'(\cdot, t) \triangleq u(\cdot, t) - \underbrace{\bar{u}}_{\triangleq \phi_0} \approx \sum_{i=1}^N b_i(t) \phi_i \approx \sum_{i=1}^n b_i(t) \phi_i$$

PROPER ORTHOGONAL DECOMPOSITION



CLASSICAL APPROACHES

$$\forall i, \frac{db_i}{dt} = i_i + l_{.i} b_{1:n} + b_{1:n}^t c_{..i} b_{1:n}$$

Problem :

Non-linear systems require too many modes.

Classical solutions : Eddy viscosity

$$l_{.i} \leftarrow \frac{\nu}{\nu_m} l_{.i}$$

- ▶ Constant ν (Aubry *et al.* (1988))
- ▶ Modal ν_i (Rempfer & Fasel (1994))
- ▶ ν or $\nu_i \propto \|b_{1:n}\|_2$ (Östh *et al.* (2014))
- ▶ $\nu \propto f\left(\|b_{1:n}\|_2^2\right)$ (Protas *et al.* (2014))

OUR APPROACH

Our approach :

▶ $dX_t = wdt + \sigma dB_t$

▶ $w = \sum_{i=0}^n b_i \phi_i$

(in the truncated subspace)

▶ $\sum_{i=n+1}^N b_i \phi_i dt$ a realization of σdB_t

(in the complementary "small-scale" subspace)

ESTIMATION OF a

We look for a decomposition of $a = \sum_{i=0}^n b_i(t)z_i(x)$.

- ▶ Reduced subspace with coherent time scales
- ▶ No need to reconstruct a
- ▶ Autonomous system

Indeed, $\frac{\partial w}{\partial t} = I + L(w) + C(w, w) + D(a, w)$ becomes :

$$\frac{db_i}{dt} = \int_{\Omega} \phi_i \cdot \left(I + \sum_{p=0}^n L(\phi_p)b_p + \sum_{p,q=0}^n (C(\phi_p, \phi_q) + D(\phi_p, z_q)) b_p b_q \right)$$

ESTIMATION OF a

$$\forall x \in \mathbb{R}^d, \quad \sum_{i=n+1}^N b_i(t) \phi_i(x) \Delta t = (u(x, t) - w(x, t)) \Delta t$$

realization of $d\tilde{X}_t^x \triangleq \sigma(x, t) dB_t$ (reminder : $a = \sigma \sigma^t$)

$$\begin{aligned} z_i(x) &= \int_0^T \frac{b_i(t)}{\lambda_i T} a(x, t) dt \\ &= \int_0^T \frac{b_i(t)}{\lambda_i T} d \langle \tilde{X}^x, (\tilde{X}^x)^t \rangle_t \\ &= \mathbb{P} - \lim_{\Delta t \rightarrow 0} \sum_{t_i=0}^T \frac{b_i(t_i)}{\lambda_i T} \left(\tilde{X}_{t_{i+1}}^x - \tilde{X}_{t_i}^x \right) \left(\tilde{X}_{t_{i+1}}^x - \tilde{X}_{t_i}^x \right)^t \end{aligned}$$

- Estimator with good statistical properties (Rao (1999))
(when the projection subset is well chosen)

PLAN

INTRODUCTION

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REDUCED MODEL

RESULTS

Data

Turbulence modes z_i

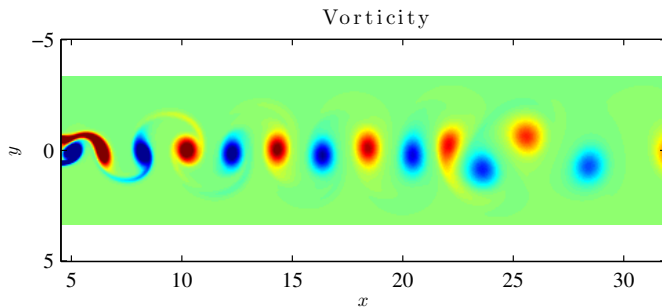
Reconstruction of temporal modes

CONCLUSION

DATA

Wake behind a cylinder

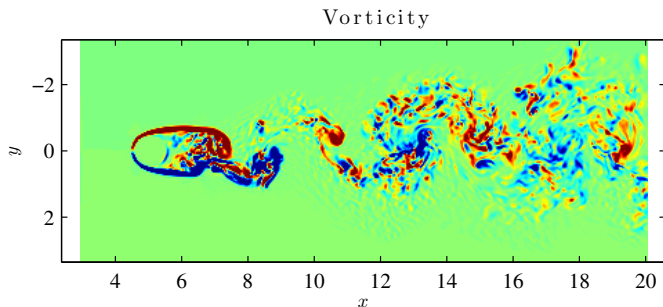
- ▶ at Reynolds 300 : 2D flow



DATA

Wake behind a cylinder

- ▶ at Reynolds 300 : 2D flow
- ▶ at Reynolds 3900 : 3D flow



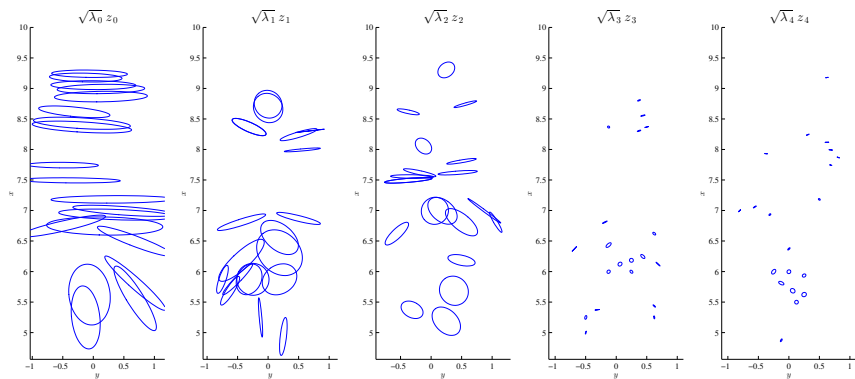
TURBULENCE MODES z_i 

FIGURE : Local spectral representations of the matrix $z_i(x, y, 0)$, normalized by $\sqrt{\lambda_i} = \sqrt{b_i^2}$, from the 2D flow (Re=300).

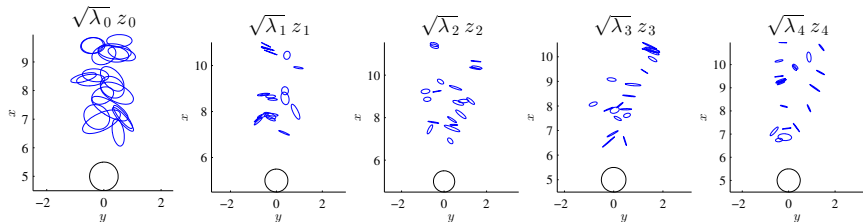
TURBULENCE MODES z_i 

FIGURE : Local spectral representations of the matrix $z_i(x, y, 0)$, normalized by $\sqrt{\lambda_i} = \sqrt{b_i^2}$, for some some point $(x, y, 0)$ of the horizontal section at $z = 0$, from the 3D flow ($Re=3900$).

RECONSTRUCTIONS OF TEMPORAL MODES

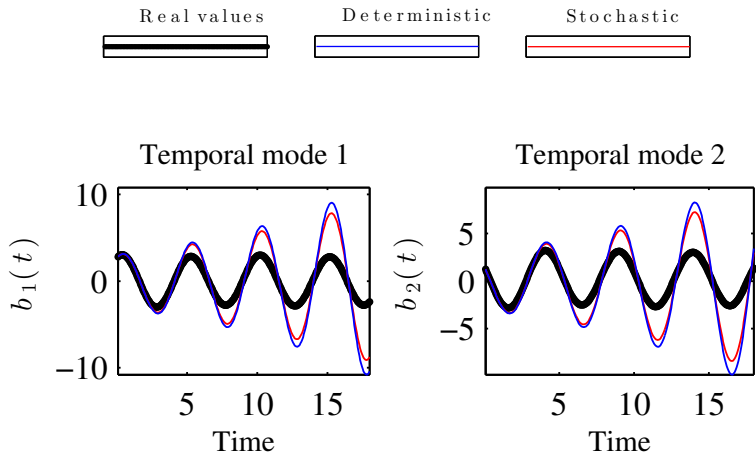


FIGURE : $n=2$ and $Re=3900$ (3D flow).

RECONSTRUCTIONS OF TEMPORAL MODES

Increase of a estimation :

$\frac{\partial w}{\partial t} = I + L(w) + C(w, w) + D(a, w)$ becomes :

$$\frac{db_i}{dt} = \int_{\Omega} \phi_i \cdot \left(I + \sum_{p=0}^n L(\phi_p) b_p + \sum_{p,q=0}^n (C(\phi_p, \phi_q) + \alpha D(\phi_p, z_q)) b_p b_q \right)$$

RECONSTRUCTIONS OF TEMPORAL MODES

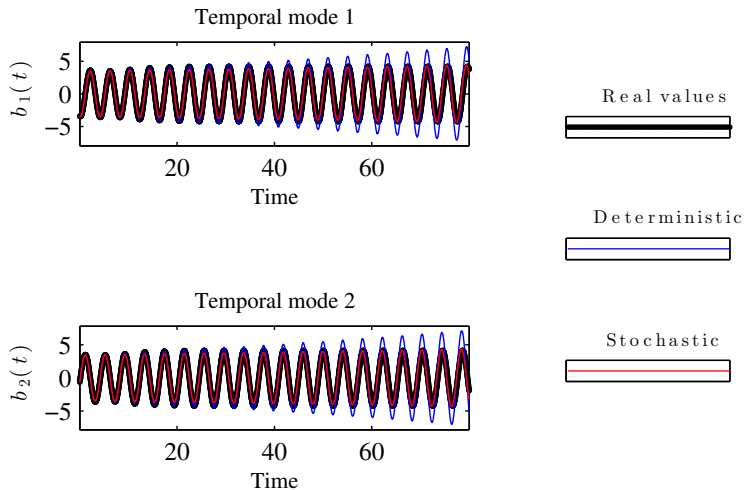


FIGURE : $n=2$ and $Re=300$ (2D flow).

RECONSTRUCTIONS OF TEMPORAL MODES

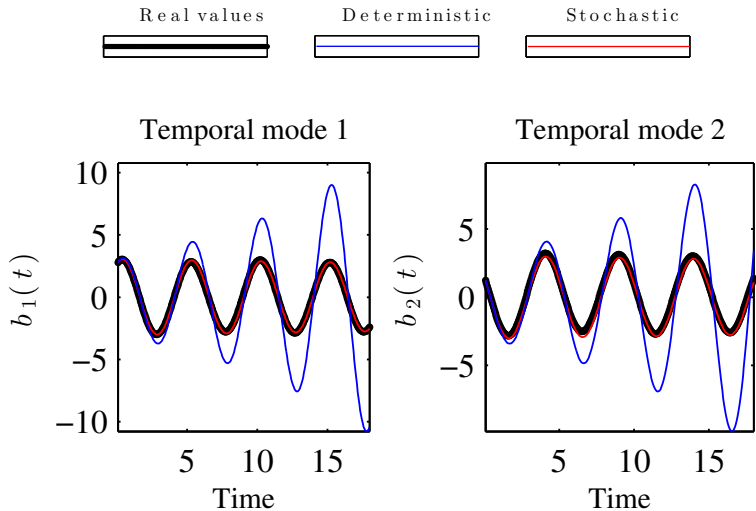


FIGURE : $n=2$ and $Re=3900$ (3D flow).

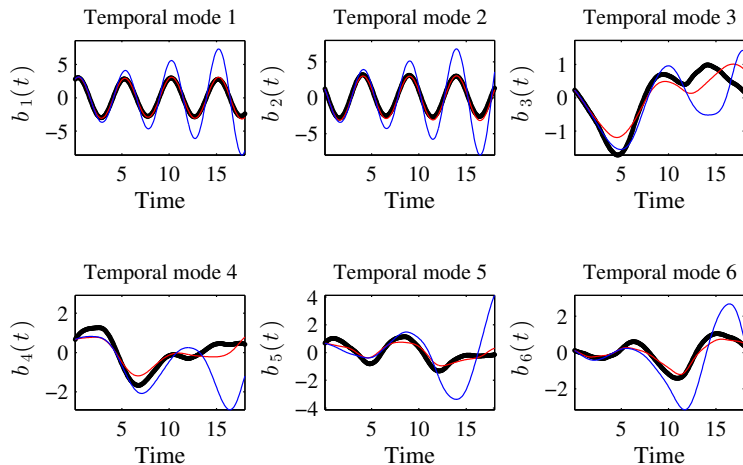
RECONSTRUCTIONS OF TEMPORAL MODES

Modal increase of a estimation :

$\frac{\partial w}{\partial t} = I + L(w) + C(w, w) + D(a, w)$ becomes :

$$\frac{db_i}{dt} = \int_{\Omega} \phi_i \cdot \left(I + \sum_{p=0}^n L(\phi_p) b_p + \sum_{p,q=0}^n (C(\phi_p, \phi_q) + \alpha_{iq} D(\phi_p, z_q)) b_p b_q \right)$$

RECONSTRUCTIONS OF TEMPORAL MODES

FIGURE : $n=6$ and $Re=3900$ (3D flow).

PLAN

INTRODUCTION

STOCHASTIC FLUID DYNAMIC MODEL

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RESULTS

CONCLUSION

SUMMARY

- ▶ Building of a complete physical fluid dynamic model with few assumptions
- ▶ Local variance-covariance matrix $a(x, t)$ projected on large-scale velocity POD-modes :
Simple autonomous reduced model and physical analysis of turbulence
- ▶ Direct application on POD-Galerkin model :
Encouraging results
But, the time-decorrelated part of the small-scale random velocity seems not enough energetic
- ▶ Corrective coefficient or matrix :
Simple method with great results

FURTHER WORK

- ▶ w semi-martingale :
which implies non-Gaussian and partially temporally-correlated random small-scale velocity
- ▶ Stochastic oceanic models : Geostrophic, Shallow water, Boussinesq, QG, SQG, ...
- ▶ Estimation of a by Kriging estimation of measurements errors (SSH)

QUESTIONS

Thank you for your attention

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