Modelling fishing vessels movement and activity.

Pierre Gloaguen[1], Stéphanie Mahevas[1], Etienne Rivot[2], Mathieu Woillez [3,2],
Jérôme Guitton[2], Youen Vermard[4] et Marie-Pierre Etienne[5]

Introduction

Characterizing spatial distribution of fishing effort on a fine spatial scale is crucial to assess fishing mortalities accurately to understand fishermen's reactions to management measures and improve the assessment of the impact of management plans. In this context, IFREMER developed the RECOPESCA project with volunteer fishermen, whose vessels positions were recorded at a 15 minute time step. To analyse these observed trajectories, mechanistic mathematical models allows the understanding of movement drivers and the identification of the sequence of hidden (non observed) behaviors. Identifying these different behaviors adopted by vessels during a fishing trip (route towards fishing zone, fishing activity...) is of interest to understand what drives fishing activities and fishing effort dynamics.

The continuous path of fishing vessels is modelled considering movement characteristics such as velocities for instance, conditionally to the behavioral state. These models are commonly called Hidden Markov Models (Rabiner, 1989). We propose to describe the vessel's path using the Ornstein Ulhenbeck process (OUP). This model is equivalent, when considered at discrete and regular time steps, to an Auto-Regressive (AR) process. Analysing the results, waves patterns in observed speed processes create problems of identification. Using the physical model ECOMARS 3D, these patterns can be removed removed as they are results of tide currents.

FIGURE 1 : Bottom trawler

Describing fishing vessels movement and activity.

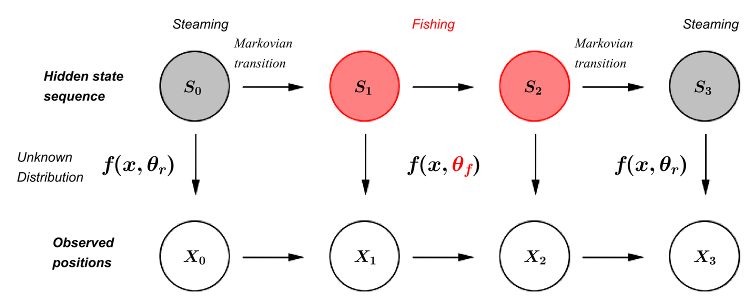
Framework : Hidden Markov Model

Observed positions are ruled by

- A sequence of hidden behaviors (fishing or steaming).
- This sequence is a Markov chain.

Observed positions are results of the hidden sequence through an unknown distribution (figure 2).

FIGURE 2 : Formal representation of a HMM



Estimation $\rightarrow \hat{\theta}_r, \hat{\theta}_f$, and estimated hidden state sequence

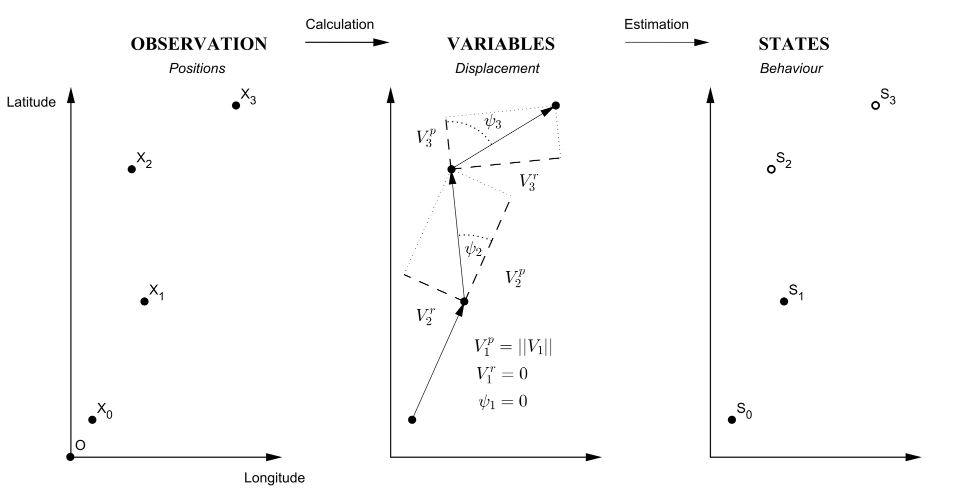
Decomposing trajectories

From recorded positions $X_1 \dots X_N$, calculate

- Mean speeds $V_1 \dots V_N$
- Turning angles $\psi_1 \dots \psi_N$
- 2-dimensional velocity process $\begin{pmatrix} V_j^p \\ V_j^r \end{pmatrix} = \begin{pmatrix} V_j \cos \psi_j \\ V_j \sin \psi_j \end{pmatrix}$, $j = 1 \dots N$

Velocity will be the studied process (figure 3).

FIGURE 3 : Calculating velocity process from observed positions in order to estimate hidden behaviours.



Model for the velocity process

The velocity process in a given activity is assumed to solve a stochastic differential equation.

$$dV_t = \rho(\gamma - V_t)dt + \zeta dW_t$$

With a regular discrete time step, it is equivalent to an AR process :

$$V_{t+1}^p | (S_{t+1} = i) = \eta_{p,i} + \mu_{p,i} V_t^p + \sigma_{p,i}\epsilon_{p,t}$$
$$V_{t+1}^r | (S_{t+1} = i) = \eta_{r,i} + \mu_{r,i} V_t^r + \sigma_{r,i}\epsilon_{r,t}$$

Inference

Estimating movement parameters

- 2 states model (steaming and fishing) .

$\Rightarrow \theta = 14$ parameters to estimate.

To estimate θ : $\rightarrow$ EM algorithm.

- Iterative algorithm to calculate MLE
- from an estimator θ_n, compute and maximize (see figure 4) :

$$Q(\theta|\theta_n) = \mathbb{E}_{S|X,\theta_n}(\log(L(\theta; X, S))).$$

Estimating hidden behavior sequence

To estimate the sequence of hidden behaviors. (fishing activity) $\rightarrow$ Viterbi algorithm. It computes iteratively :

$$\hat{S} = \text{argmax}_{s_0 \dots s_T}\left(p(s_0 \dots s_T,\ X_0 \dots X_T|\hat{\Theta})\right)$$

Obtaining confidence intervals

Bootstrap methods : Simulating new trajectories from $\hat{\theta}$ and re-estimating parameters. $\rightarrow$ The more time consuming step.

Data

- IFREMER's RECOPESCA Project
- Vessels performing in the Channel in 2007-2010.
- Positions recorded every 15 minutes (GPS).
- Bottom trawl, trammel nets, dredge.
- 4 examples of trajectories (figure 5).

FIGURE 4 : Formal representation of the EM algorithm

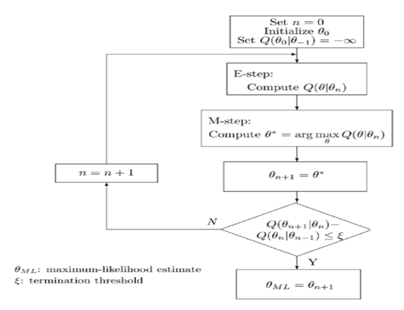
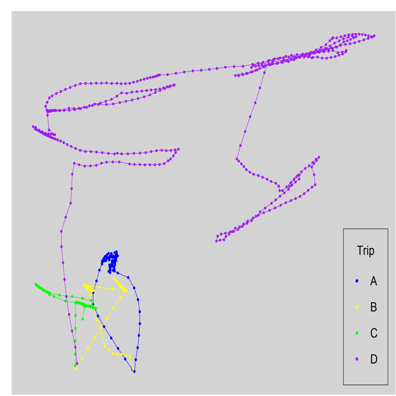


FIGURE 5 : 4 trips issued from RECOPESCA project.



Simulation approach

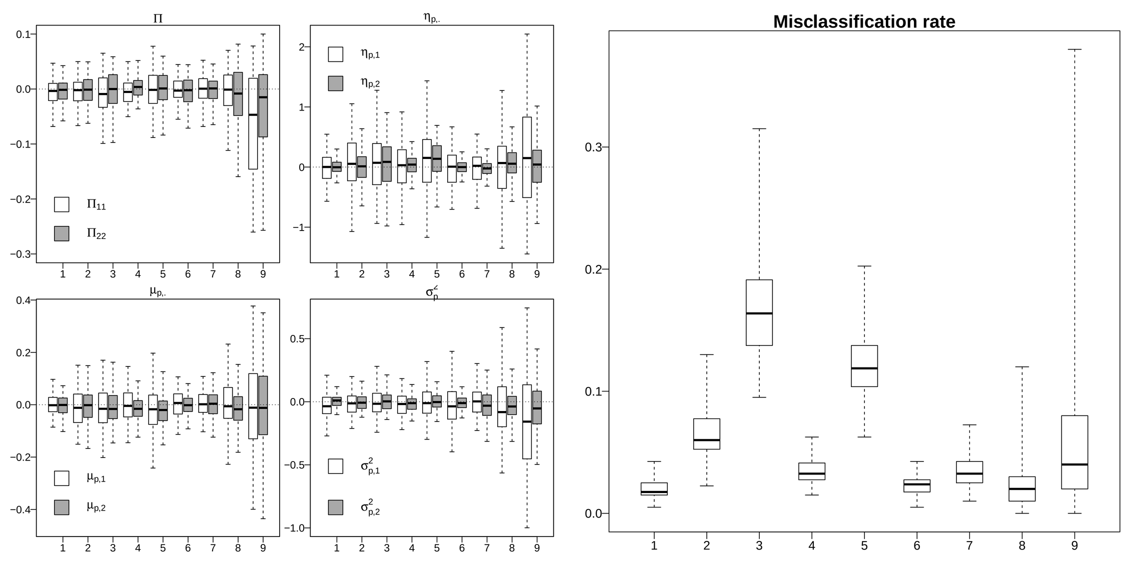
- Test quality of estimation on different scenarios.
- Identify influence of parameters range on estimation.
- Identify problematic scenarios.
- 9 scenarios tested (table 1)

TABLE 1 : Simulation scenarios.

		η (1 2)	μ (1 2)	σ^2 (1 2)	$\mathbb{E}$ (1 2)	$\mathbb{V}$ (1 2)	n
1	p r	$\begin{pmatrix} 6 & 1 \\ 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 0 & 0.5 \\ 0 & 0.2 \end{pmatrix}$	$\begin{pmatrix} 1 & 0.5 \\ 0.5 & 0.1 \end{pmatrix}$	6 2 0 0	1 0.7 0.5 0.1	400
2	p r	$\begin{pmatrix} 6 & 2 \\ 0 & 0 \end{pmatrix}$			6 4 0 0		
3	p r	$\begin{pmatrix} 6 & 3 \\ 0 & 0 \end{pmatrix}$			6 6 0 0		
4	p r	$\begin{pmatrix} 6 & 1 \\ 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 0 & 0.6 \\ 0 & 0.2 \end{pmatrix}$	$\begin{pmatrix} 1 & 0.5 \\ 0.5 & 0.1 \end{pmatrix}$	6 2.5 0 0	1 0.8 0.5 0.1	400
5	p r		$\begin{pmatrix} 0 & 0.8 \\ 0 & 0.2 \end{pmatrix}$		6 5 0 0	1 1.4 0.5 0.1	
6	p r	$\begin{pmatrix} 6 & 1 \\ 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 0 & 0.5 \\ 0 & 0.2 \end{pmatrix}$	$\begin{pmatrix} 2 & 0.5 \\ 1 & 0.1 \end{pmatrix}$	6 2 0 0	2 0.7 1 0.1	400
7	p r			$\begin{pmatrix} 1 & 1 \\ 0.5 & 0.5 \end{pmatrix}$		1 1.3 0.5 0.5	
8	p r	$\begin{pmatrix} 6 & 1 \\ 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 0 & 0.5 \\ 0 & 0.2 \end{pmatrix}$	$\begin{pmatrix} 1 & 0.5 \\ 0.5 & 0.1 \end{pmatrix}$	6 2 0 0	1 0.7 0.5 0.1	100
9	p r						50

Results on simulations

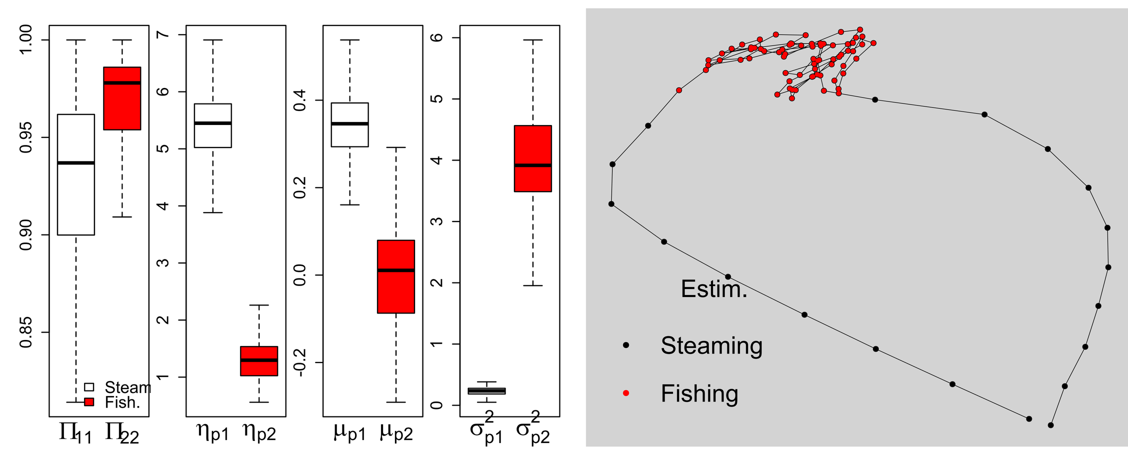
FIGURE 6 : Boxplots of results obtained for simulations



- Need of good separation between steaming and fishing processes.
- Need of a small σ^2 parameter.
- Importance of length of trajectory.

Results on data

FIGURE 7 : Boxplots of results obtained for simulations



Steaming state	*Fishing state*
Persistent (large Π_{11})	Persistent (large Π_{22})
Fast (large $\eta_{p,1}$), estimated mean : 8.4 knots	Slow (small $\eta_{p,1}$), estimated mean : 2.6 knots
Lightly autocorrelated ($\mu_{p,1}$)	No autocorrelation
Low variability (small σ_{p1}) in persistence speed $\Rightarrow$ Mvt in a straight line at regular speed.	High variability (large σ_{p1}) in persistence speed $\Rightarrow$ Mvt is erratic at irregular speed.
20% of time spent	80% of time spent

Conclusions

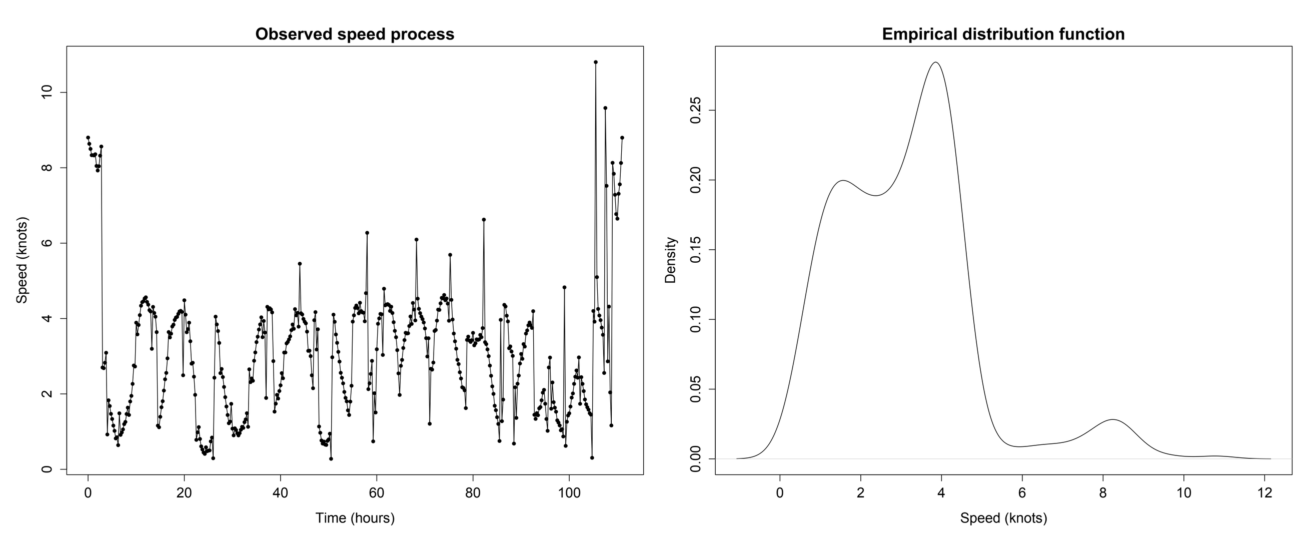
- General model to describe fishing boat activity.
- Autocorrelation might capture unwanted phenomenon.

Integrating tide currents to study speed process

Problem

Highly autocorrelated speed processes are observed, resulting on wavy patterns on time series, and on a 3-modal speed distribution (figure 8).

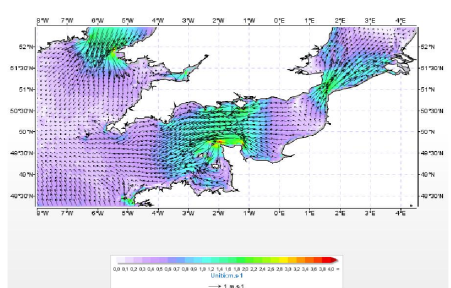
FIGURE 8 : An observed speed process highly autocorrelated (Bottom trawler, 22 meters, in the Channel, 2010)



Hypothesis

- Strong tide currents in the Channel
- May create the acceleration/deceleration patterns.
- Use of MARS 3D model to test the hypothesis (figure 9).

FIGURE 9 : Exemples of tide currents predictions from model MARS 3D www.previmer.org.



Method

MARS 3D

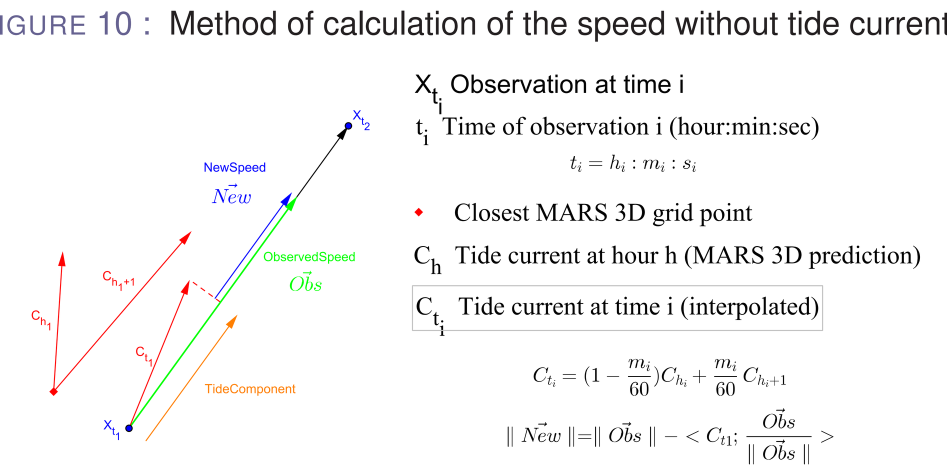
- Grid : 1 point each 4 km.
- Time Step : 1 prevision every hour.
- Only surface current considered.

Interpolation

- Position $X_t \leftrightarrow$ Closest point of MARS 3D grid
- Observation recorded at time h :m $\leftrightarrow$ Weighted by prediction at hour h and hour (h+1) (weight by minute m).

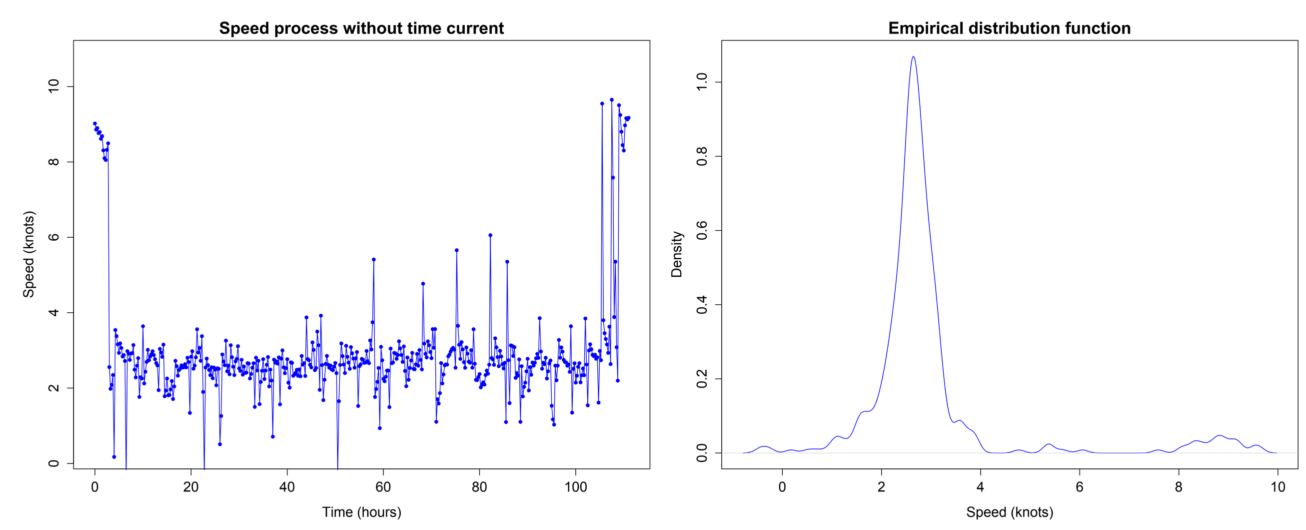
See figure 10

FIGURE 10 : Method of calculation of the speed without tide currents.



Results

FIGURE 11 : The same speed process than figure 8, without tide currents.



- Wave patterns have disappeared.
- The speed distribution has now a clear mode between 2 and 3 knots.

$\Rightarrow$ In the channel, studying speed processes implies to remove tide currents.

Perspectives

- Application to a wider fleet with VMS data.
- Using stochastic differential equations (SDE) to describe fishing vessels activity in continuous time.
- Including environmental covariables such as habitat map of target species.
- Performing a realistic simulation model for fishing boats dynamics in the Channel.

References

- Y.Vermard, E.Rivot, S.Mahevas, P.Marchal,and D.Gascuel
  Identifying fishing trip behaviour and estimating fishing effort from VMS data using Bayesian Hidden Markov Models.
  Ecological Modelling, 2010.
- P.Gloaguen, S.Mahevas, E.Rivot, M.P.Etienne, M.Woillez, J.Guitton and Y.Vermard
  An autoregressive model to describe fishing boat movement and activity.
  Submitted.
- M.Woillez, P.Gloaguen, S.Mahevas, E.Rivot, J.Guitton and Y.Vermard
  Adapting Hidden Markov Models to the diversity of fishing boat movements and activities.
  In preparation.
- P.Lazure and F.Dumas
  An external–internal mode coupling for a 3D hydrodynamical model for applications at regional scale (MARS).
  Advances in Water Resources, 2008.

Remerciements

This study was funded by European project VECTORS, La Région Pays de Loire, IFREMER and Agrocampus-Ouest. Authors thanks Patrick Berthou and Emilie Leblond, leaders of RECOPESCA project, the team of PREVIMER and national research network Pathtis funded by INRA for helpful discussions.

[1]IFREMER, Centre de Nantes, Département Ecologie et Modèles pour l'Halieutique, France
[2]AGROCAMPUS OUEST, UMR 985 Ecologie et Santé des Ecosystèmes, Ecologie Halieutique, Rennes, France
[3]IFREMER, Centre de Brest, Département Sciences et Technologies Halieutiques, France
[4]IFREMER, Centre de Boulogne sur mer, Département Manche-Mer du Nord, France
[5]AGROPARISTECH, UMR MIA 518, Paris, France

E-mail: pierre.gloaguen@ifremer.fr