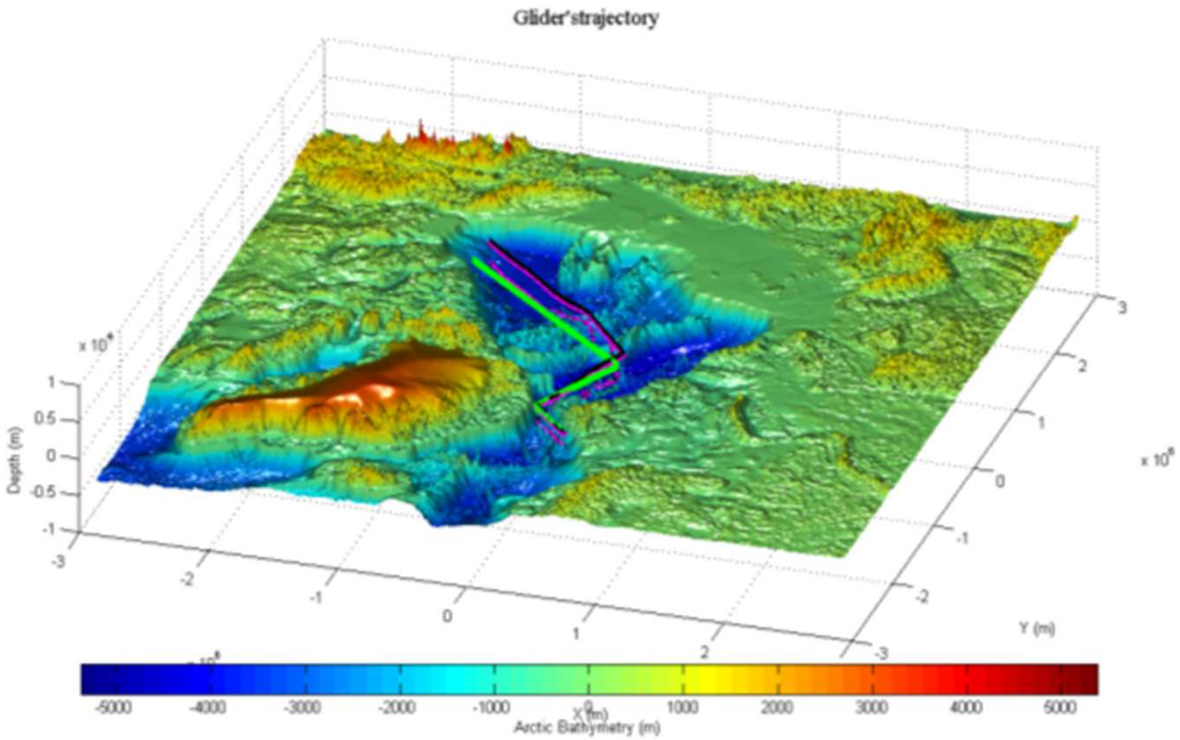
Final year project April – September 2010

Terrain Based Navigation using a Particle Filter for long range glider missions



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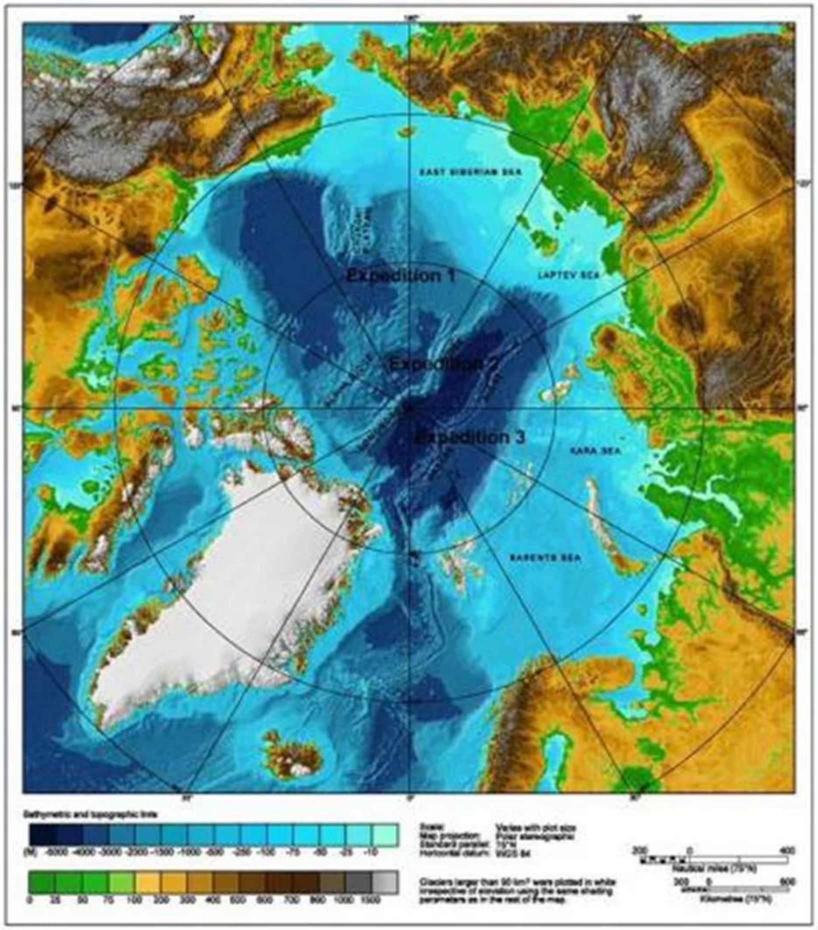
Ensi 2010 HYO

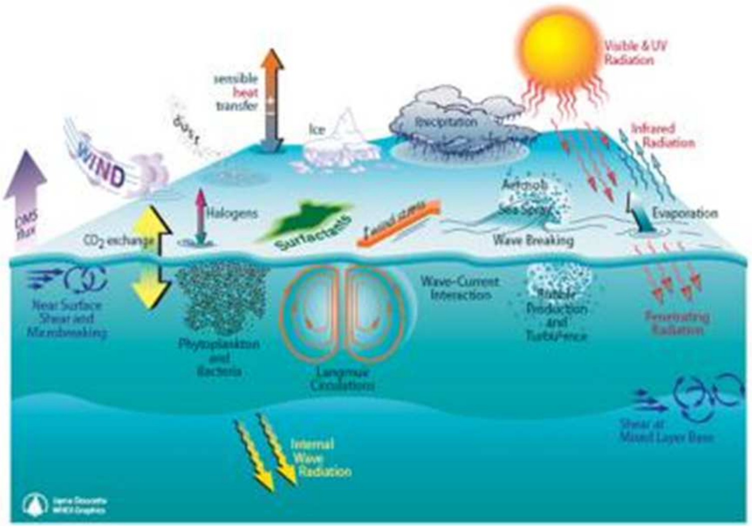
Supervisor: Dr M. Rixen

Outline

1. Introduction
2. Underwater navigation
3. Terrain Based Navigation
4. Particle Filter
5. Energy Budget
6. Simulations
7. Conclusions
8. Perspectives

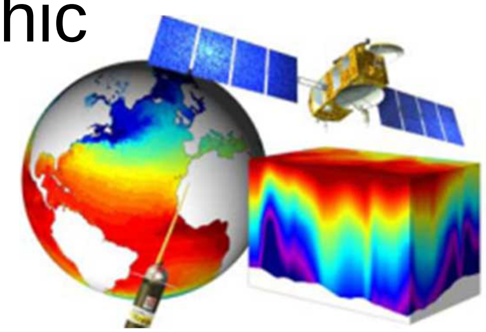


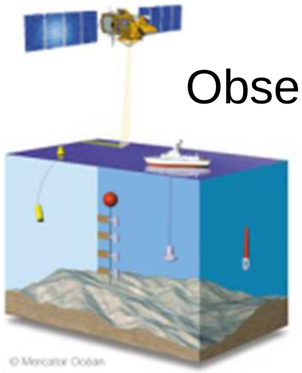
1. Introduction



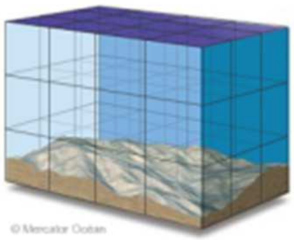
Processes operating at the air-sea interface and in the upper ocean mixed layer

- Oceans are the backbone of our ecosystem (climate, weather, fisheries)
- *In situ* data are needed to initialize, correct and validate oceanographic models

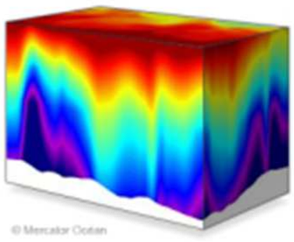




Observe



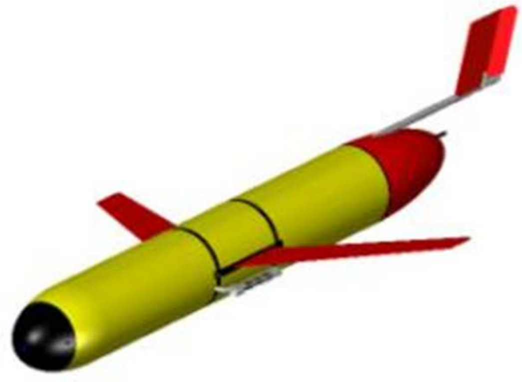
Model



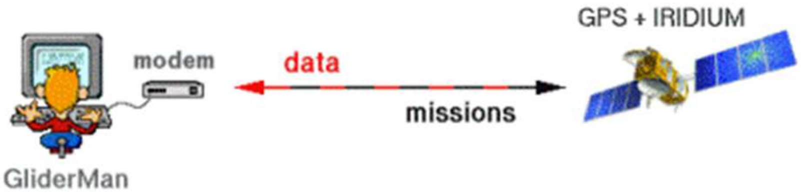
Forecast

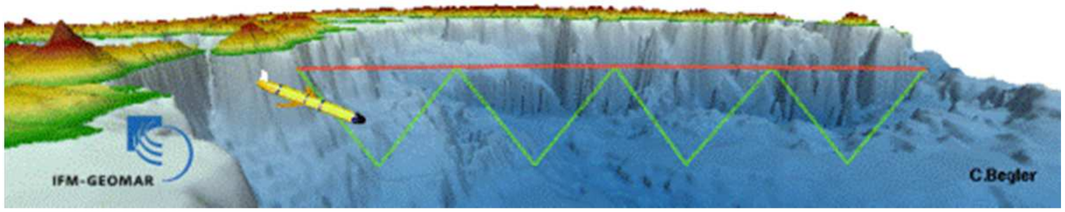
Introduction: Gliders

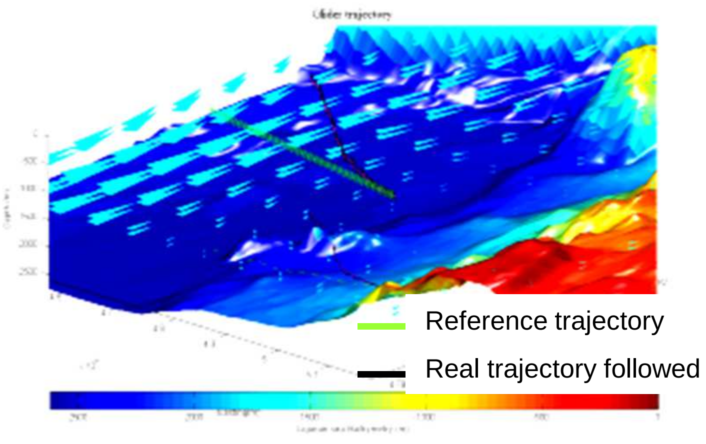
- *Gliders are unique in the AUV world*



“Gliders require no propeller and operate in a vertical saw tooth trajectory which ensures a high resolution in data sampling”
(source: Slocum glider manual)







- Varying vehicle buoyancy creates the forward propulsion

- Challenge of underwater positioning
  - ⇒ Sea currents influence

Introduction: Objectives of the project

- “Can we use a terrain navigation approach for a long range under ice mission in the Arctic Ocean?”

Effective localization and navigation is critical to successful AUV mission

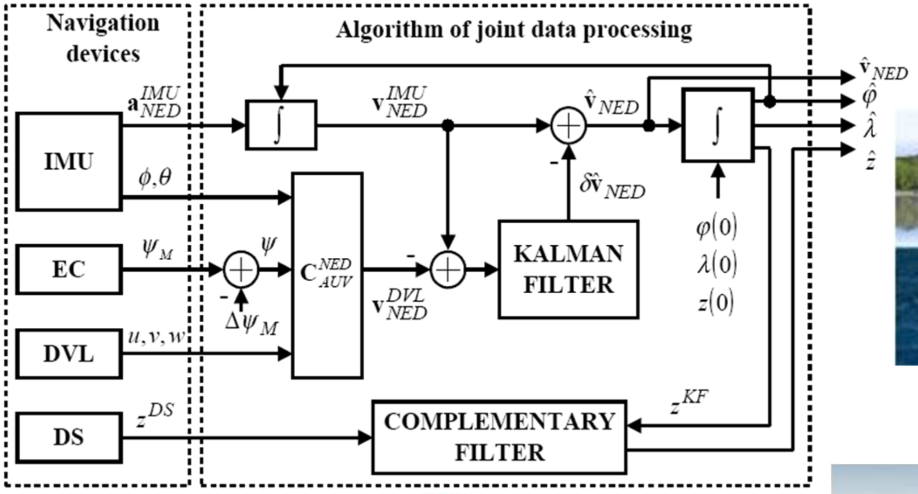
Under ice - Long range mission

- GPS fix unlikely
- Drift of position estimate
- Growing navigation uncertainty
- Limited energy budget

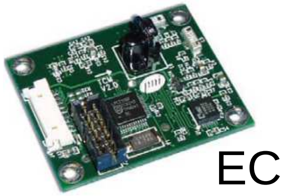
The ALTEX AUV (Atlantic Layer Tracking Experiment)

2. Underwater navigation

- Internal Navigation



IMU



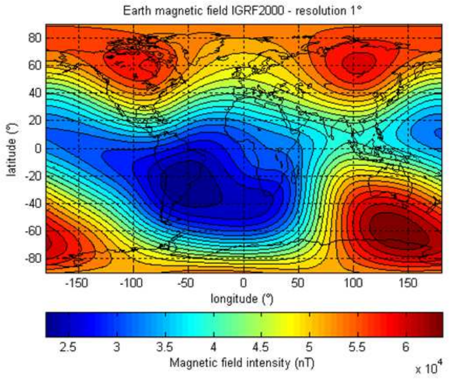
EC

DVL

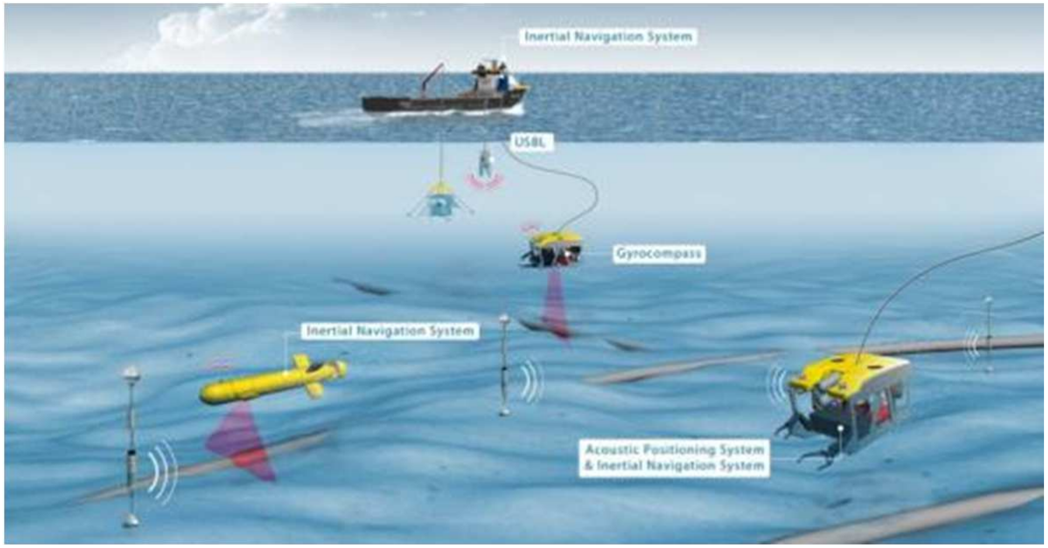
DS

- External Navigation

Ultra short baseline



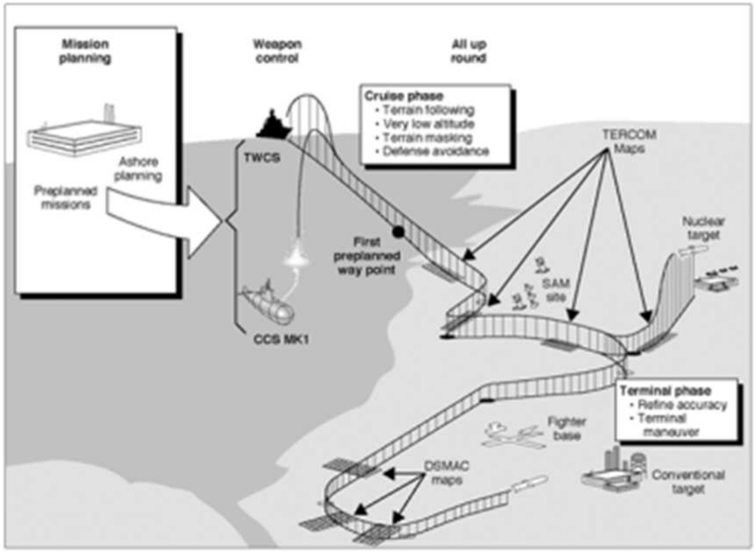
Earth's magnetic field



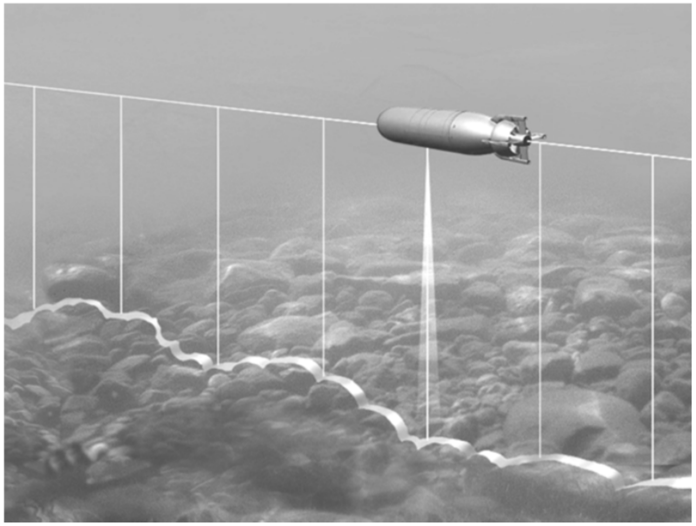
3. Terrain Based Navigation

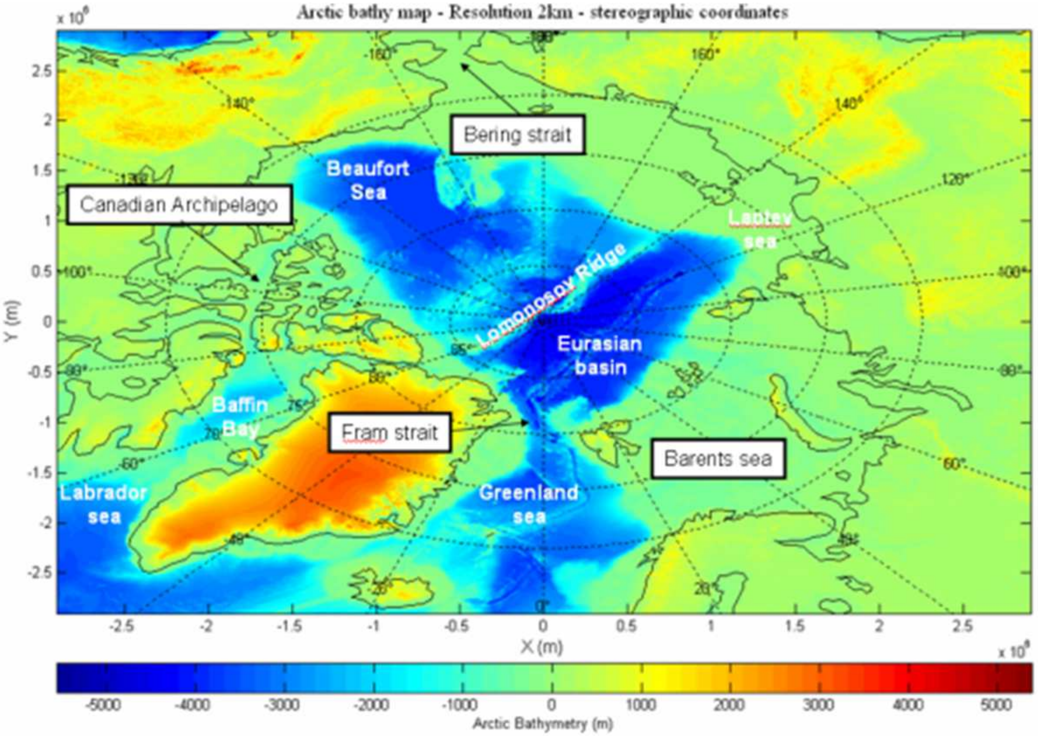
- Principle

3. Terrain Based Navigation: Principle



- Developed in 1958 to bound the error drift of cruise missile inertial navigation system



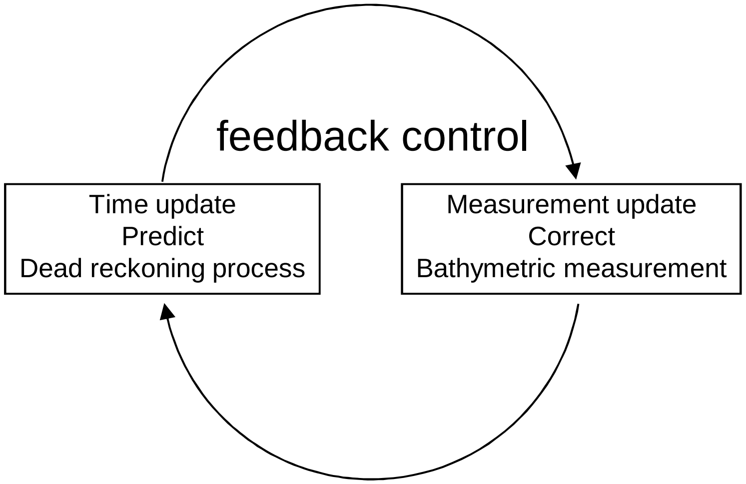


- Totally autonomous process

- Oceans seafloor represents a strong source of information

3. Terrain Based Navigation: Kalman filter?

- Assimilation of an observation (the depth of the glider) into the navigation process


feedback control

Time update
Predict
Dead reckoning process

Measurement update
Correct
Bathymetric measurement

- Measurement update

$$\hat{x}_k = \hat{x}_k^- + K(z_k - H\hat{x}_k^-)$$

$\hat{x}_k$ a posteriori state estimate

$\hat{x}_k^-$ dead reckoning estimate

z_k actual bathymetric measurement

K gain or blending factor

$H\hat{x}_k^-$ predicted measurement

Minimize the estimate error covariance

$$P_k = E[e_k e_k^T] = E[(x_k - \hat{x}_k)(x_k - \hat{x}_k)^T]$$

$$K_k = \frac{P_k^- H^T}{HP_k^- H^T + R}$$

R: Measurement noise covariance

- Time update

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1} + w_{k-1}$$

$\hat{x}_k^-$ dead reckoning estimate of the state at step k

$\hat{x}_{k-1}$: posterior probability of the state at step $k-1$

B : control input matrix

A : transition matrix

u_{k-1} : control input

w_{k-1} : process noise

But: the glider has a non linear evolution

$$\hat{x}_k^- = f(\hat{x}_{k-1}, u_{k-1}, w_{k-1})$$

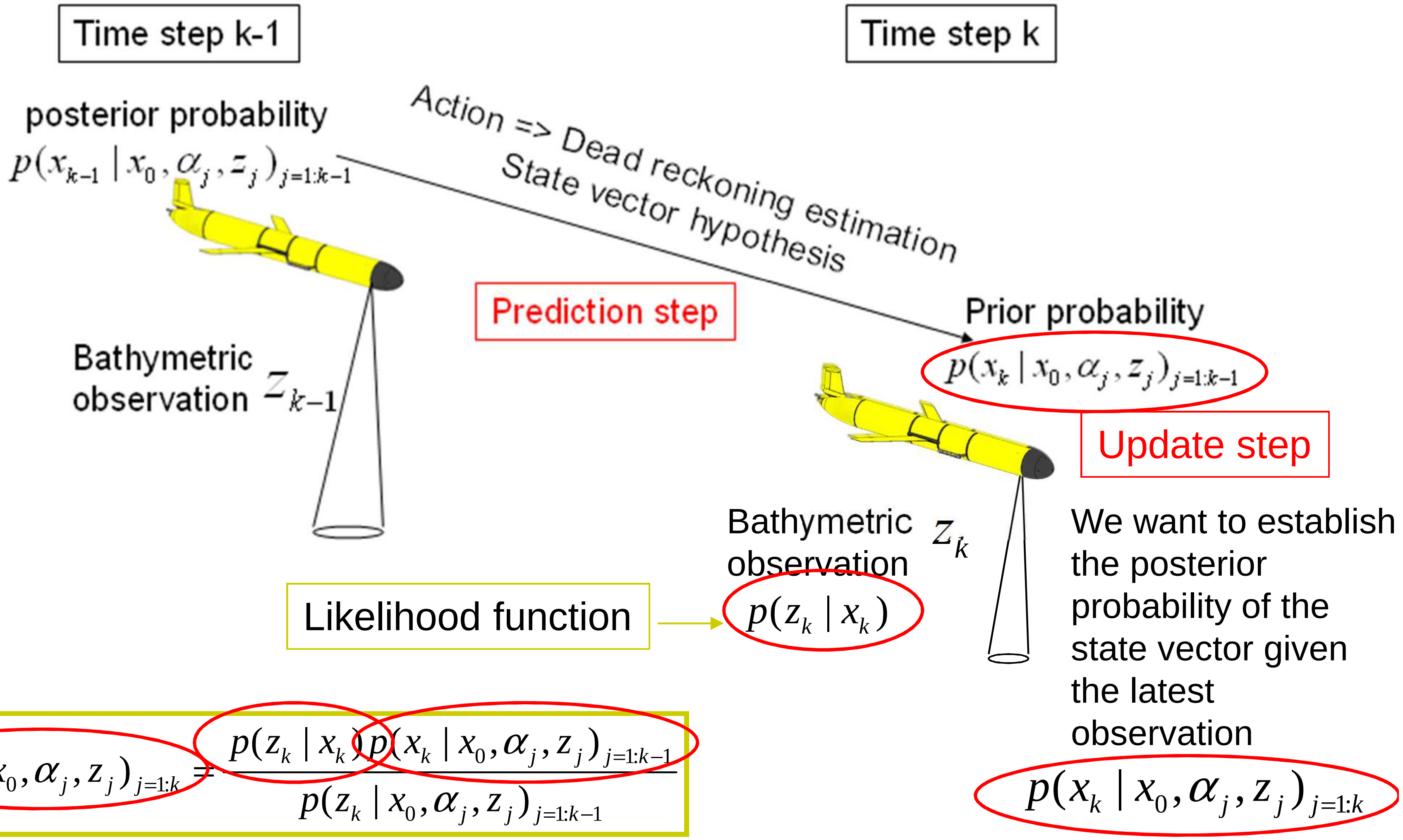
- Use of a particle filter:

⇒ multi nodal

⇒ non Gaussian

4. TBN – Particle Filter

- Bayesian framework



Time step k-1

Time step k

posterior probability $p(x_{k-1} \mid x_0, \alpha_j, z_j)_{j=1:k-1}$

Action => Dead reckoning estimation

State vector hypothesis

Prediction step

Prior probability $p(x_k \mid x_0, \alpha_j, z_j)_{j=1:k-1}$

Update step

Bathymetric observation z_{k-1}

Bathymetric observation z_k

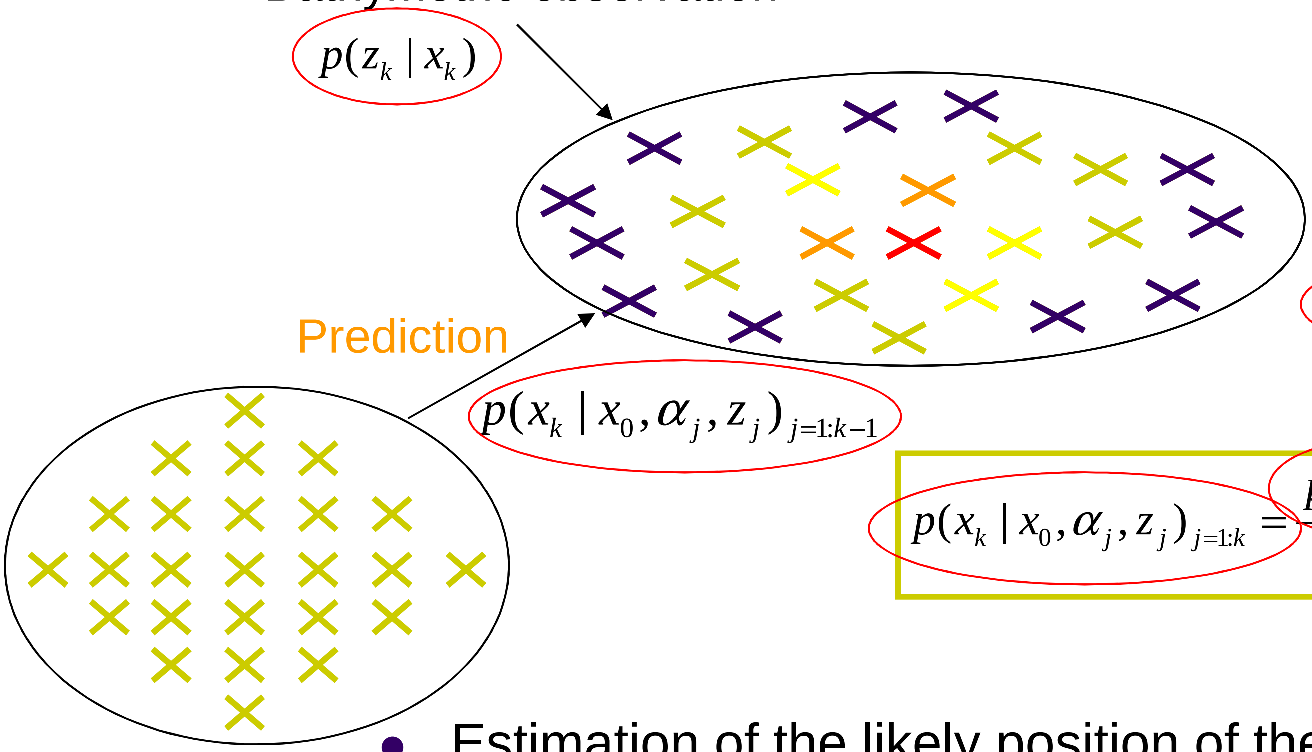
Likelihood function $p(z_k \mid x_k)$

We want to establish the posterior probability of the state vector given the latest observation

$$p(x_k \mid x_0, \alpha_j, z_j)_{j=1:k}$$

$$p(x_k \mid x_0, \alpha_j, z_j)_{j=1:k} = \frac{p(z_k \mid x_k)\, p(x_k \mid x_0, \alpha_j, z_j)_{j=1:k-1}}{p(z_k \mid x_0, \alpha_j, z_j)_{j=1:k-1}}$$

4. TBN – Particle Filter: principle



Bathymetric observation

$p(z_k \mid x_k)$

Prediction

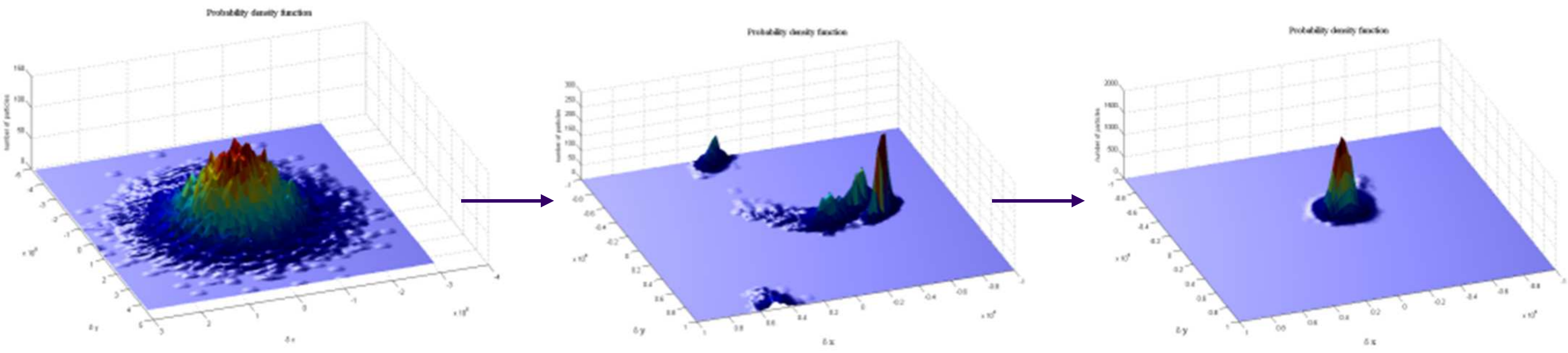
$p(x_k \mid x_0, \alpha_j, z_j)_{j=1:k-1}$

Update

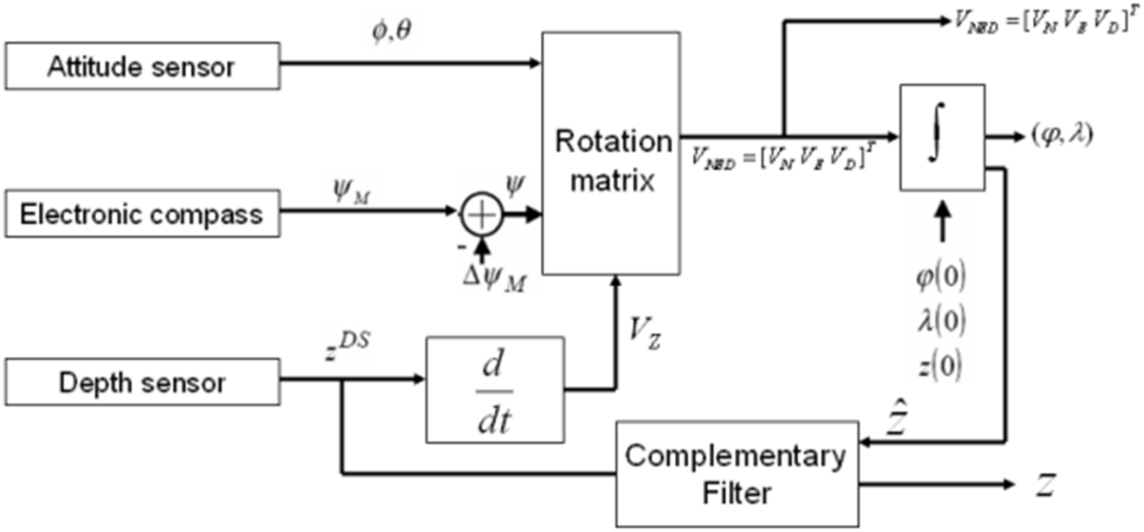
$p(x_k \mid x_0, \alpha_j, z_j)_{j=1:k}$

$$p(x_k \mid x_0, \alpha_j, z_j)_{j=1:k} = \frac{p(z_k \mid x_k)\, p(x_k \mid x_0, \alpha_j, z_j)_{j=1:k-1}}{p(z_k \mid x_0, \alpha_j, z_j)_{j=1:k-1}}$$

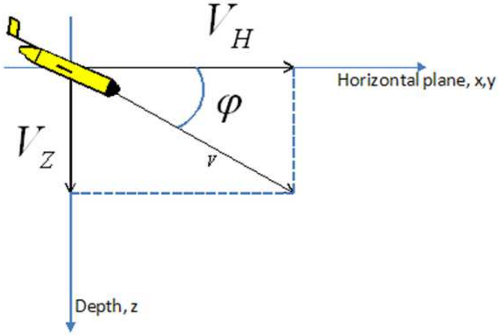
- Estimation of the likely position of the glider: weight distribution + re-sampling process

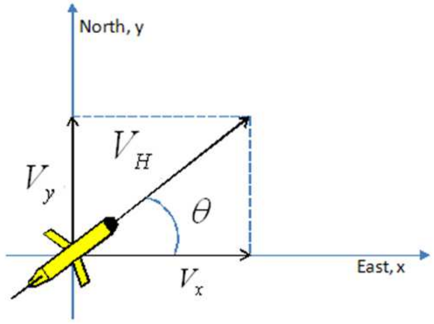


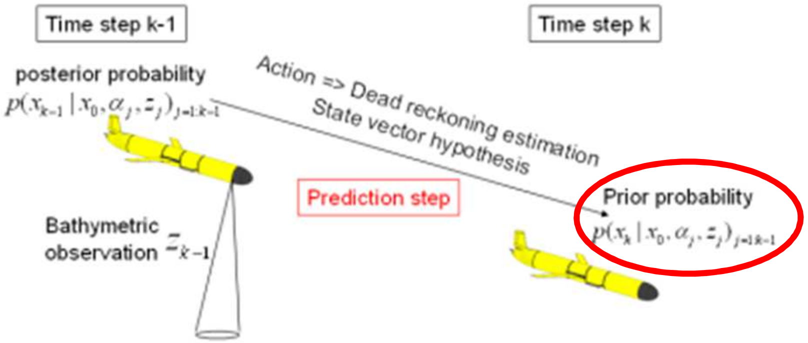
4. TBN – Particle Filter: Prediction Step



- projection forward in time using a kinematics model



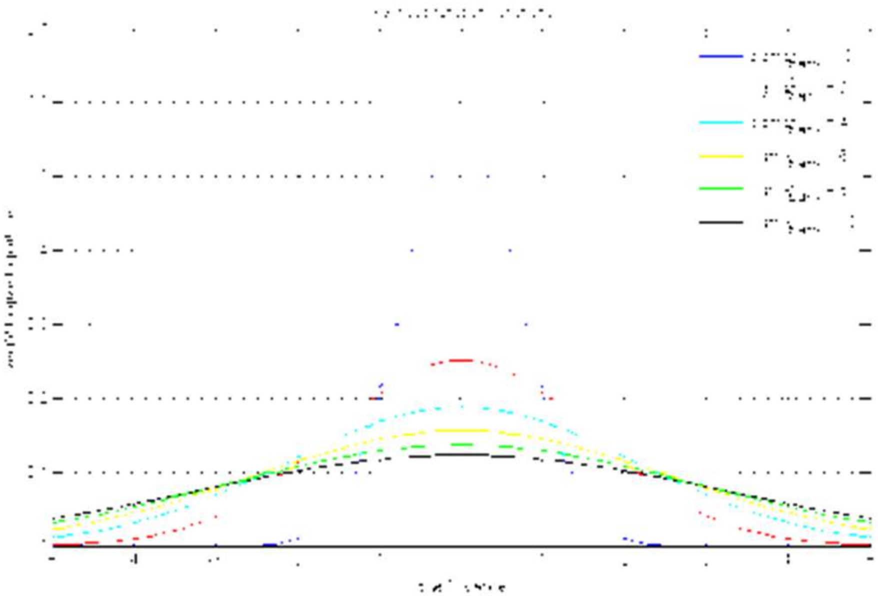


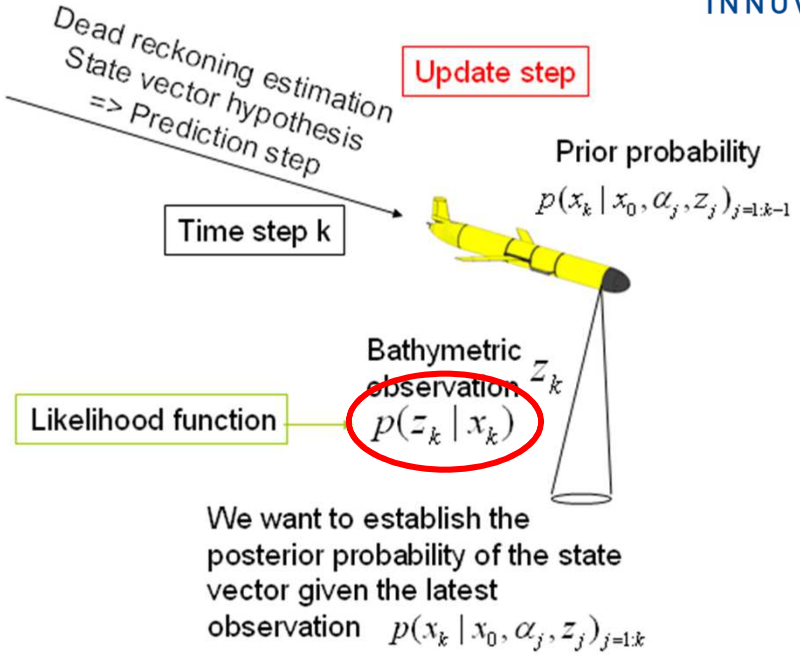


$$\boxed{p(x_k \mid x_0,\alpha_j,z_j)_{j=1:k}} \longrightarrow \begin{pmatrix} x\\ \dot{x}\\ y\\ \dot{y}\end{pmatrix}_{k+1} = \begin{pmatrix}1&\Delta T&0&0\\0&1&0&0\\0&0&1&\Delta T\\0&0&0&1\end{pmatrix}\begin{pmatrix}x\\ \dot{x}+u\\ y\\ \dot{y}+v\end{pmatrix}_k + \begin{pmatrix}0\\ \Delta V_x\\ 0\\ \Delta V_y\end{pmatrix} + chol(w_k^2 . \begin{pmatrix}\Delta T^2&\Delta T&0&0\\ \Delta T&1&0&0\\ 0&0&\Delta T^2&\Delta T\\ 0&0&\Delta T&1\end{pmatrix})$$

4. TBN – Particle Filter: Update Step

- Update the weight of each particle given the likelihood between:
  - the bathymetric measurement
  - depth seen by each particle





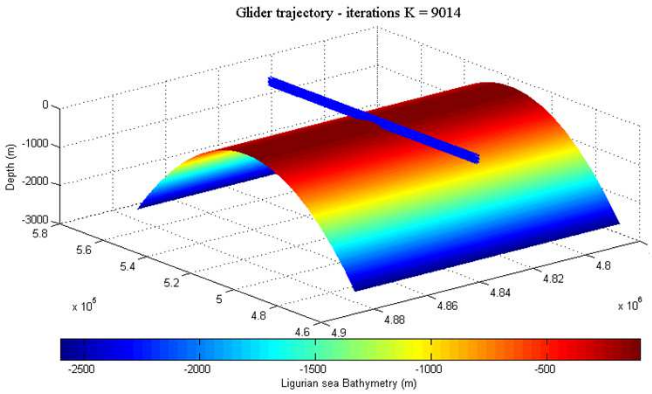
We want to establish the posterior probability of the state vector given the latest observation $p(x_k | x_0, \alpha_j, z_j)_{j=1:k}$

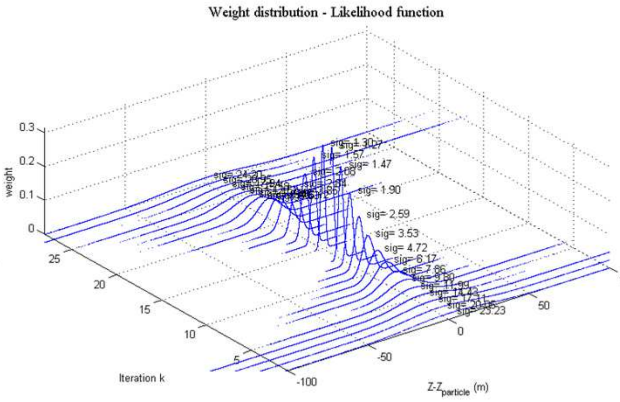
- Likelihood function

$$p(z_k | x_k) = \frac{1}{\sqrt{2\pi}.\sigma_{bathy}}.e^{\frac{-(Z-Zi)^2}{2.\sigma_{bathy}^2}}$$

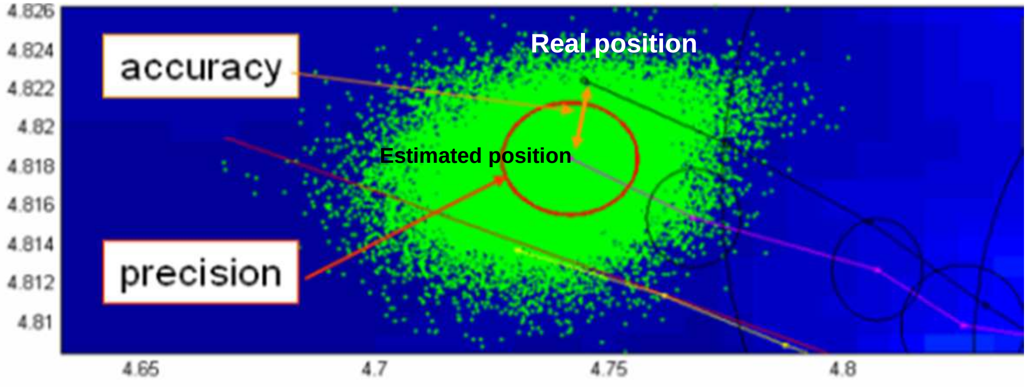
- International Hydrographic organization (IHO) – S44 order 2

$$\sigma_{bathyTVU} = \frac{1}{2}\sqrt{1^2 + (0.023z)^2}$$





4. TBN – Particle Filter: Re-sampling State estimation



- Mean: $$z_{PF} = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} z_i}$$

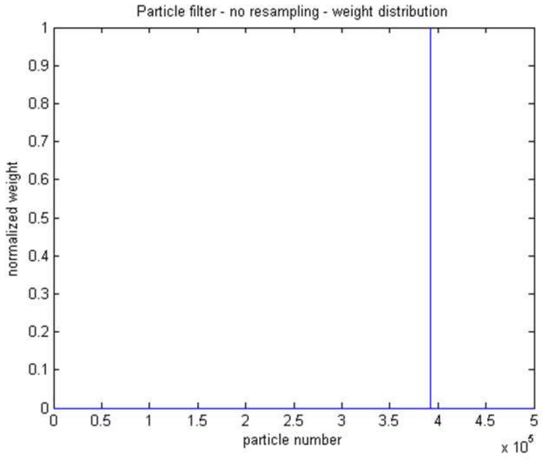
z_{PF} : estimated depth

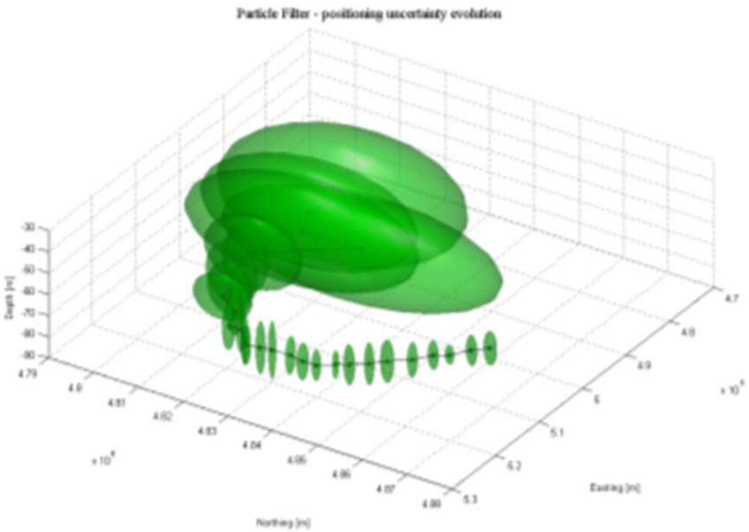
w_i : weight attributed to particle i

z_i : depth at particle “i” ’s location

- Variance: describes how far values lie from the mean

$$\mathrm{var}(Z) = \begin{pmatrix} z_1 - z_{PF} & z_2 - z_{PF} & \cdots & z_N - z_{PF} \end{pmatrix} \begin{pmatrix} w_1 & & & 0 \\ & w_2 & & \\ & & \ddots & \\ 0 & & & w_N \end{pmatrix} \begin{pmatrix} z_1 - z_{PF} \\ z_2 - z_{PF} \\ \vdots \\ z_N - z_{PF} \end{pmatrix}$$

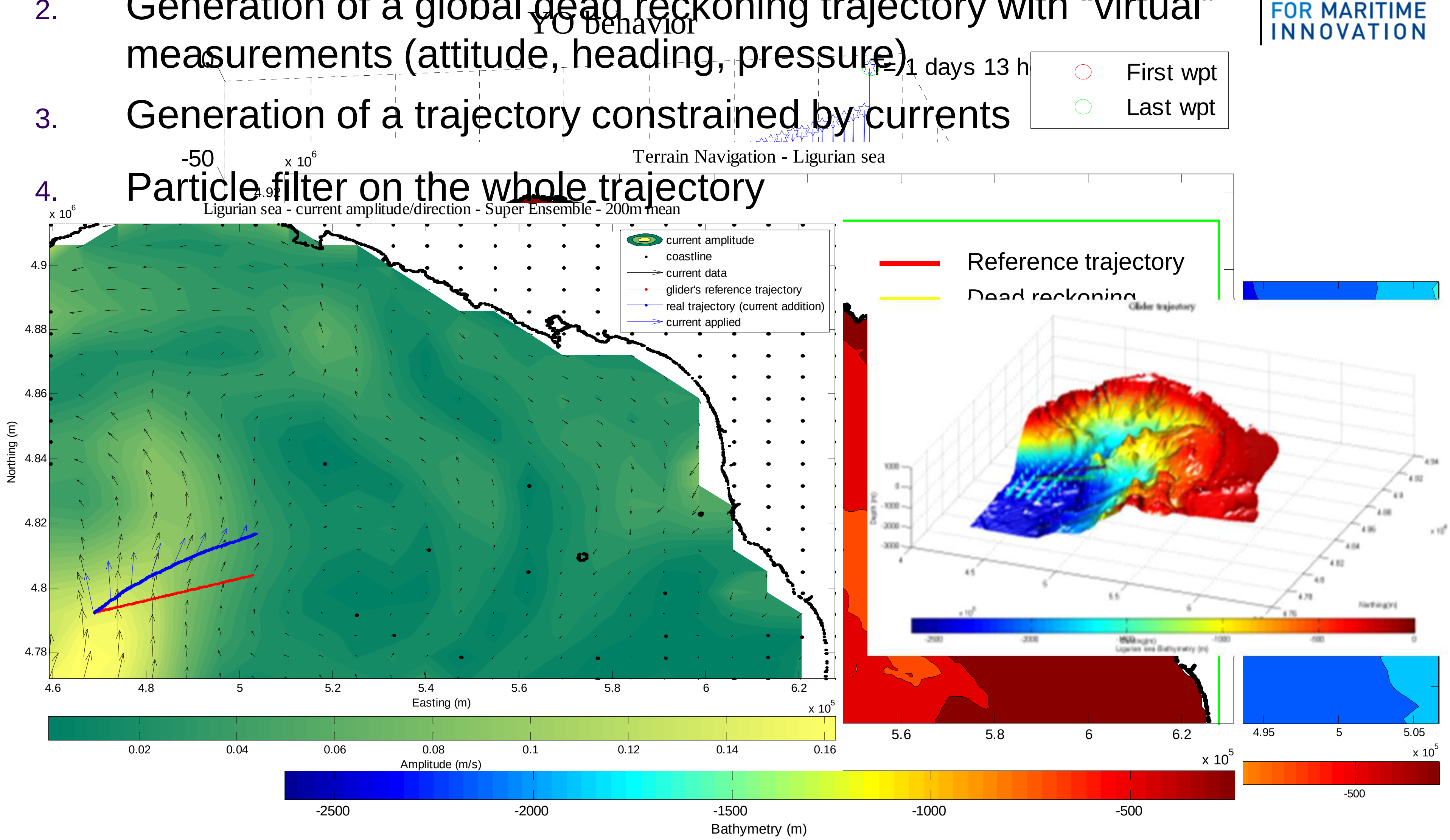




- re-sampling prevents high concentration of probability mass at a few particles

4. TBN – Particle Filter: Simulation principle

1. Generation of a reference trajectory
2. Generation of a global dead reckoning trajectory with “virtual” measurements (attitude, heading, pressure)
3. Generation of a trajectory constrained by currents
4. Particle filter on the whole trajectory



5. Energy Budget

- Mission endurance depends highly on the capacity and usage of batteries
- Tradeoff decisions between
  - energy consumption
  - Sensing
  - data processing
  - communication activities

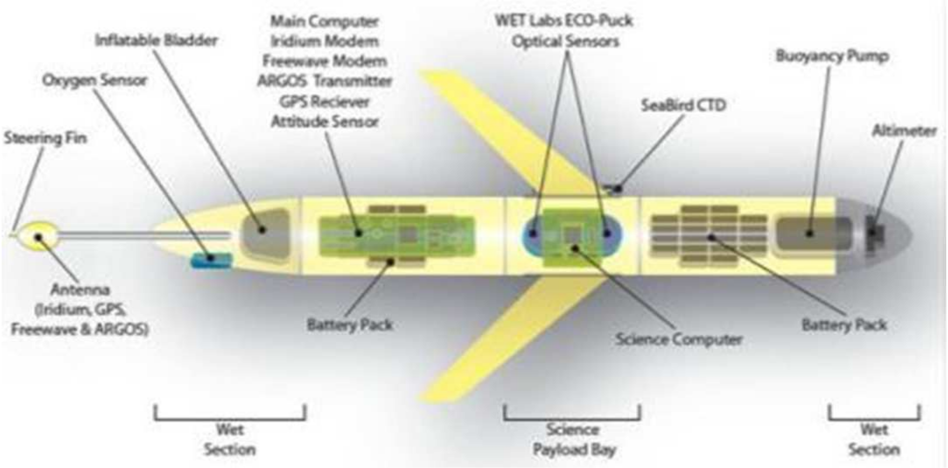
Buoyancy pump

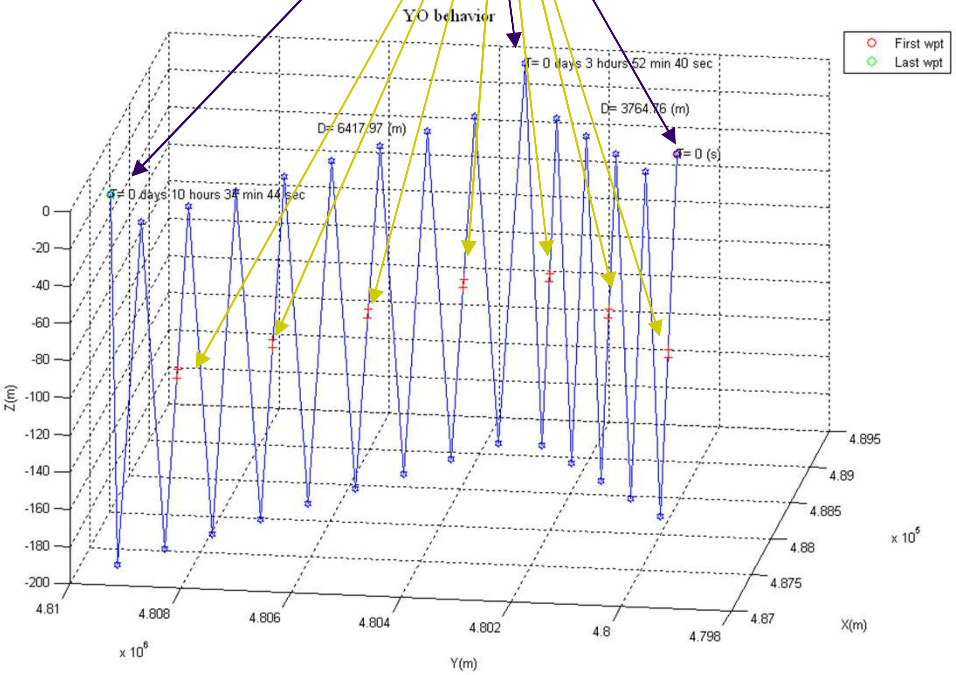
Gliders components:

- Controller
- Attitude sensor
- Pressure sensor
- Science sensors

Pinging policy:
pulse emission + data processing

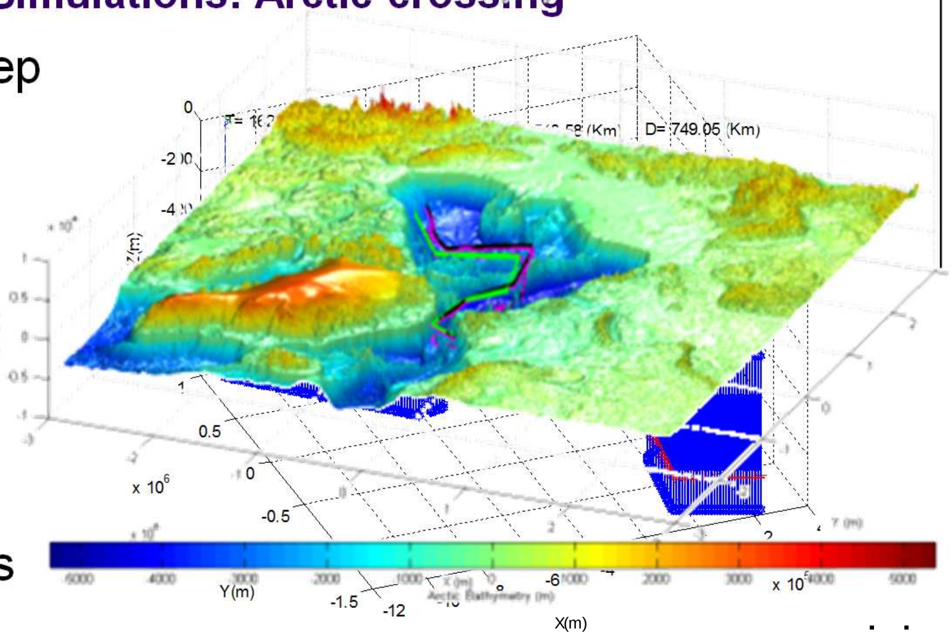
Surface behavior: GPS, irridium





6. Simulations: Arctic crossing

- Arctic crossing: Slocum deep glider (1000m)

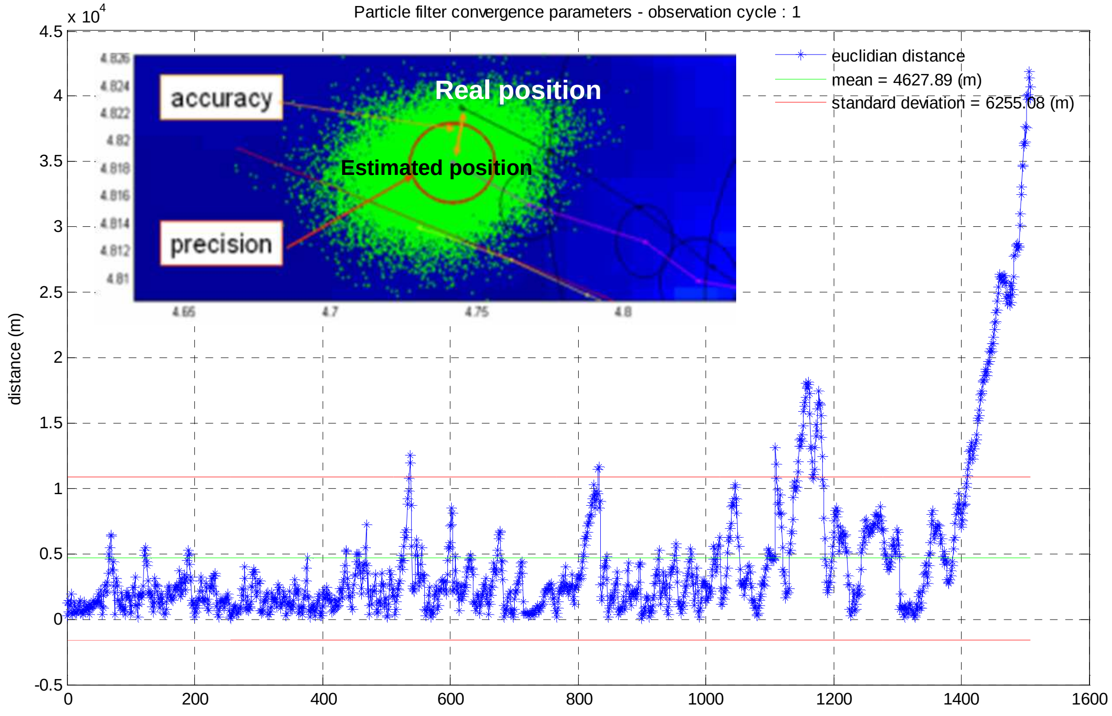


Mission specifications:

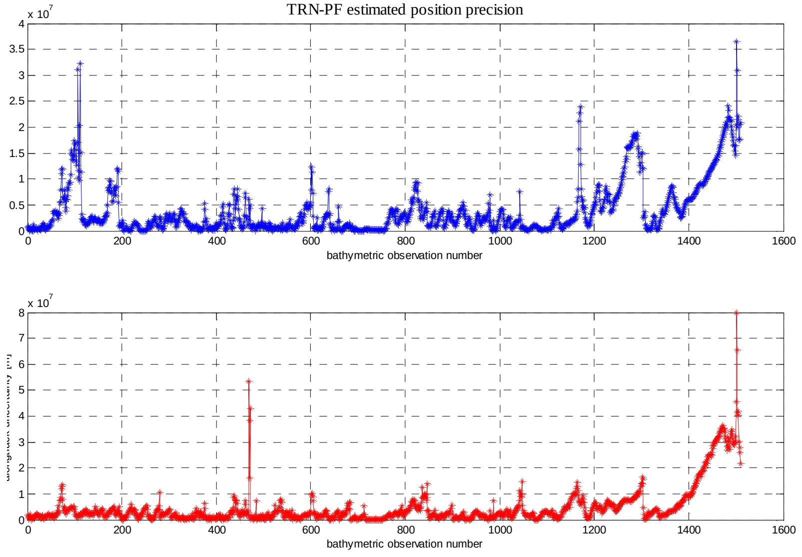
- 7 waypoints
- pitch angle: 26 degrees
- diving target depth: 1000m (when possible)
- climbing target depth: 400m
- -1 pings per dive / every dive

~ 165 days of submerged mission under the ice

- Particle filter accuracy results



- Particle filter precision results

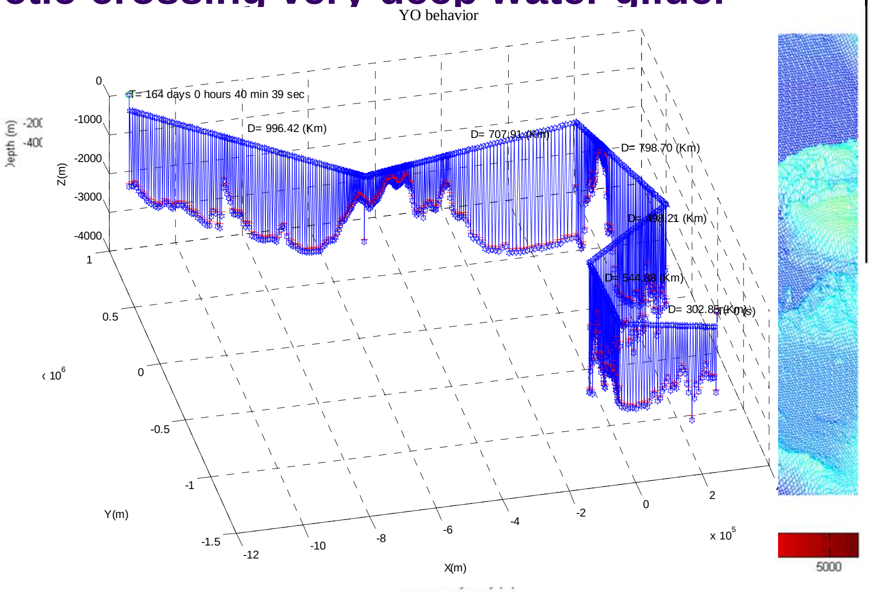


6. Simulations: Arctic crossing very deep water glider

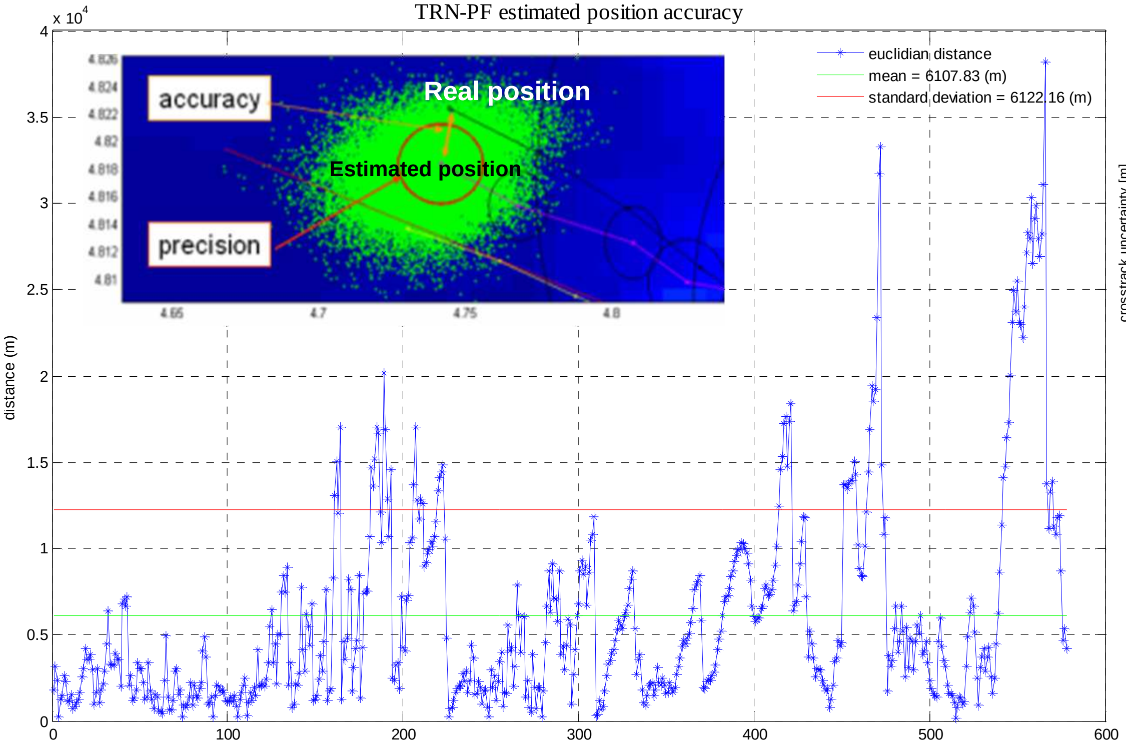
- Arctic crossing: very deep water glider (4000m)

Mission specifications:
- 7 waypoints
- pitch angle: 26 degrees
- diving target depth: 4000m (when possible)
- climbing target depth: 400m
-1 pings per dive / every dive

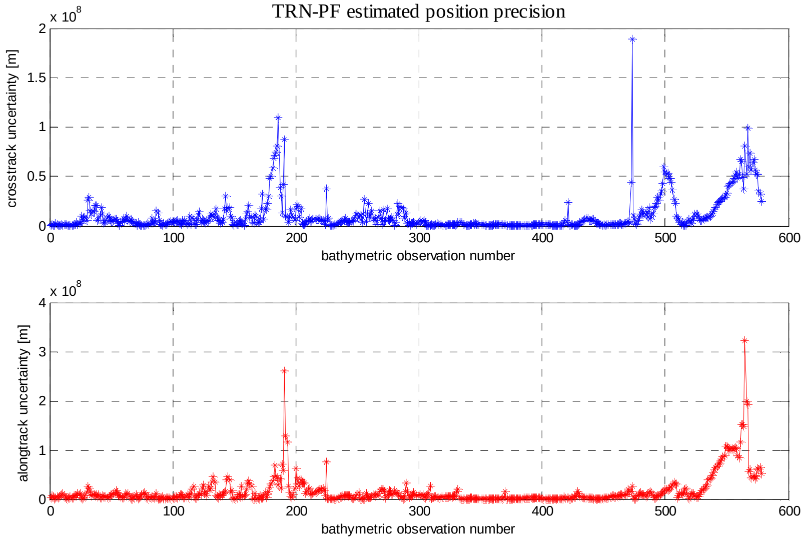
~ 165 days of submerged mission under the ice



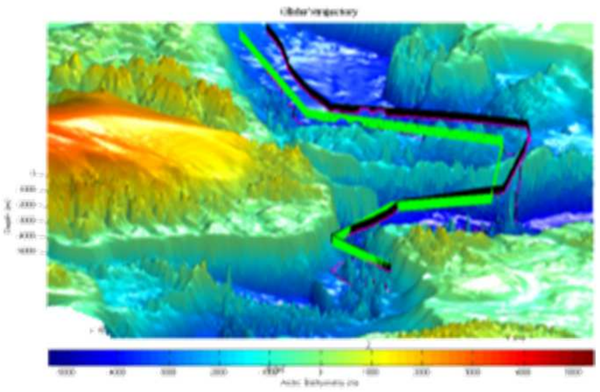
- Particle filter accuracy results



- Particle filter precision results

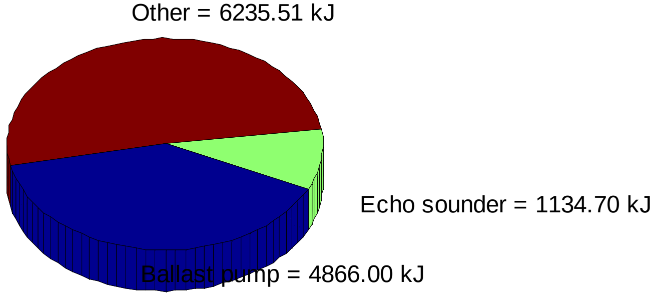


6. Simulations: Arctic crossing
Energy consumed

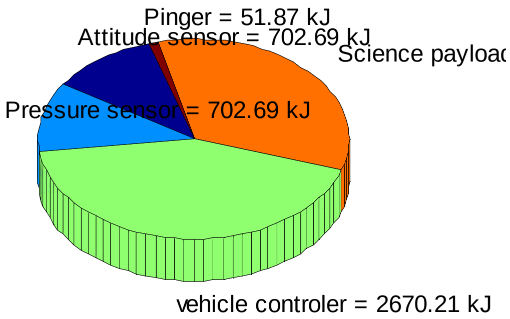


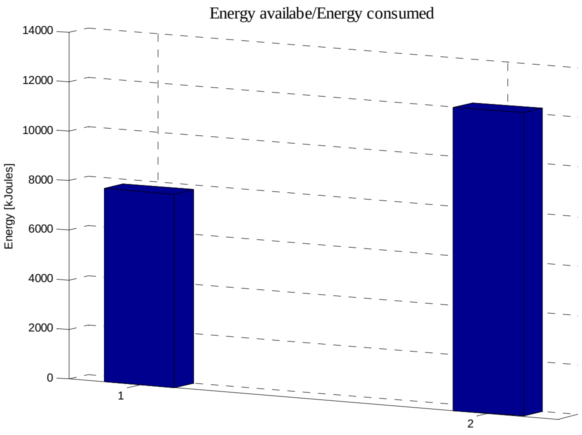
- Slocum glider (1000m)

Energy consumed repartition



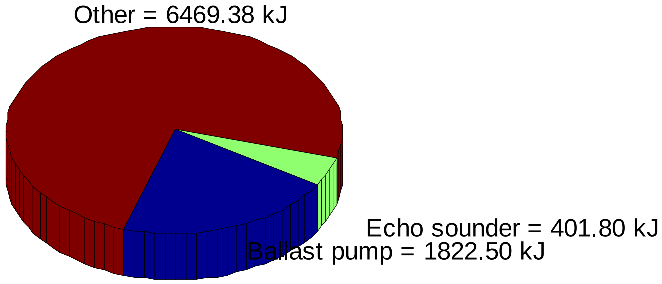
Other - low consumption sensors



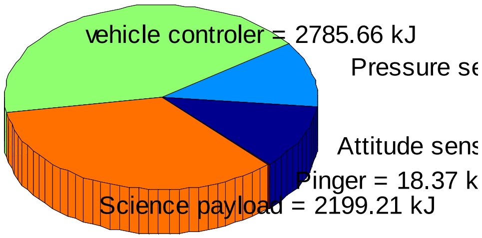


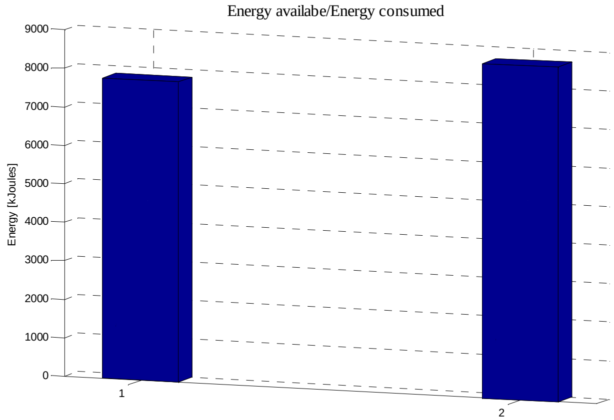
- Very deep water glider (4000m)

Energy consumed repartition



Other - low consumption sensors



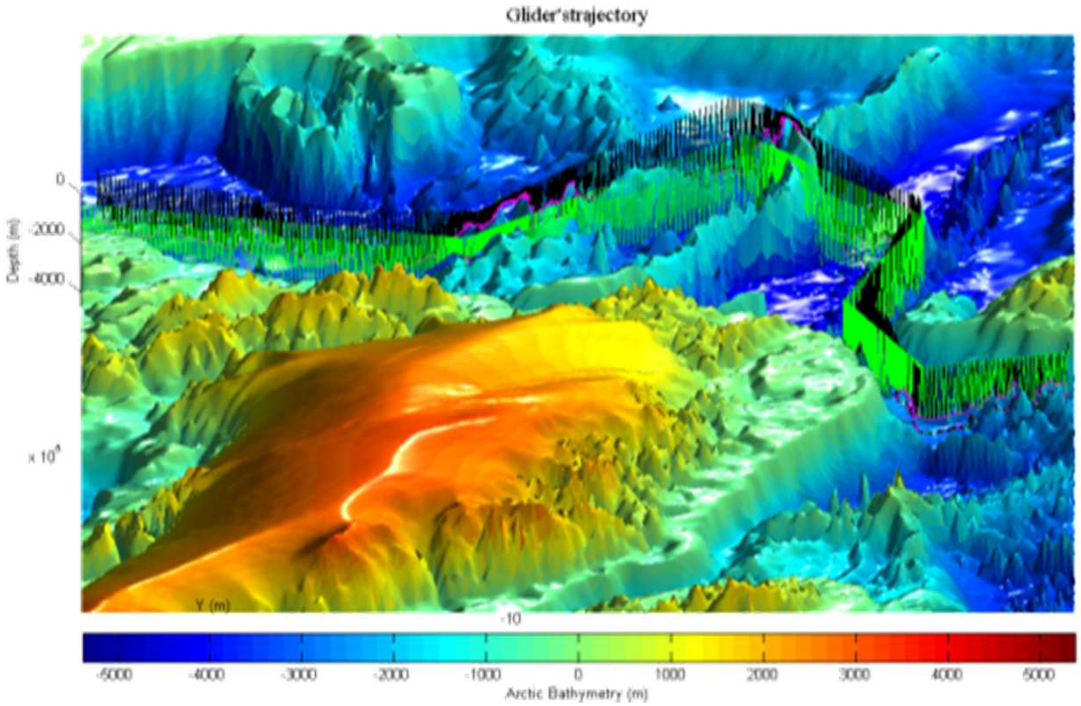


Conclusion

- “Can we use a terrain navigation algorithm for a long range under ice mission in the Arctic Ocean?”

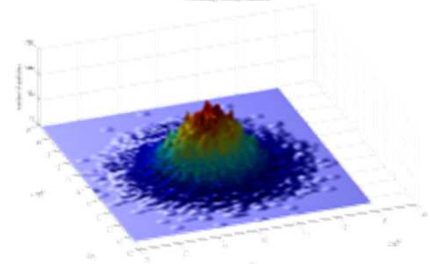
  - Simulation results show that the TBN principle using a particle filter seems to be a perfect tradeoff to meet:

1. Accurate navigation
2. Limited endurance
3. Low cost technology

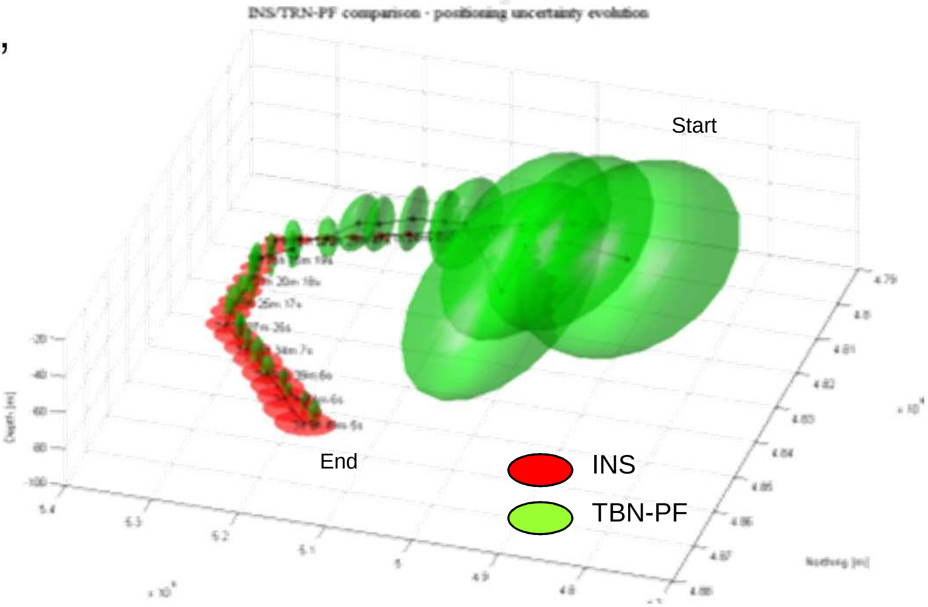


Conclusion

1. an accurate, precise and independent positioning estimation process
2. a limited endurance
3. a low cost technology

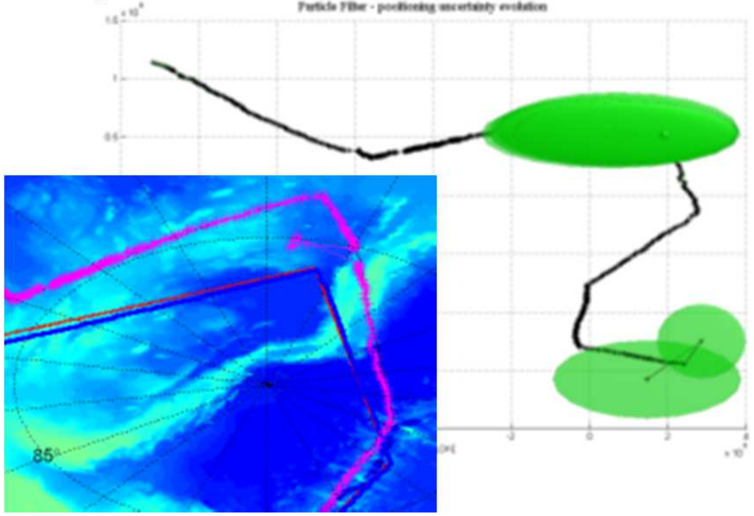


The particle filter works in a Bayesian framework

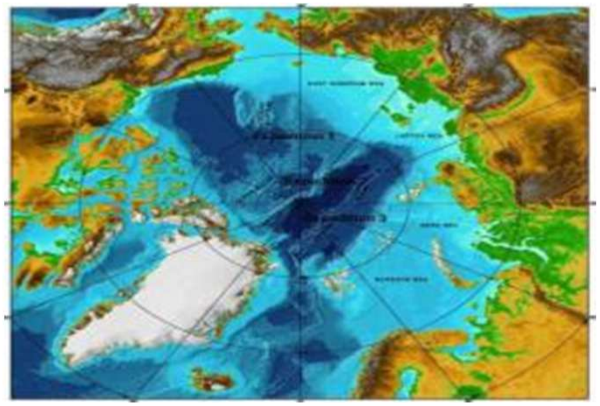


A tracking process “independent of time”

Ability to detect fake track



Accuracy and Precision of the particle filter navigation estimation are linked to:
- The resolution of the bathymetric chart
- The unique variability of the seafloor



Conclusion

1. an accurate, precise and independent positioning estimation process
2. a limited endurance
3. a low cost technology

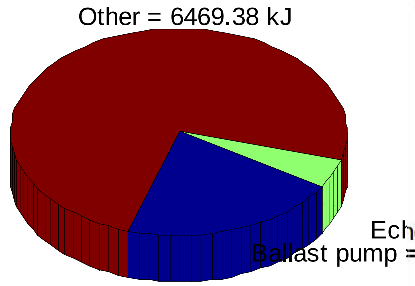
Most of gliders operates solely on battery power

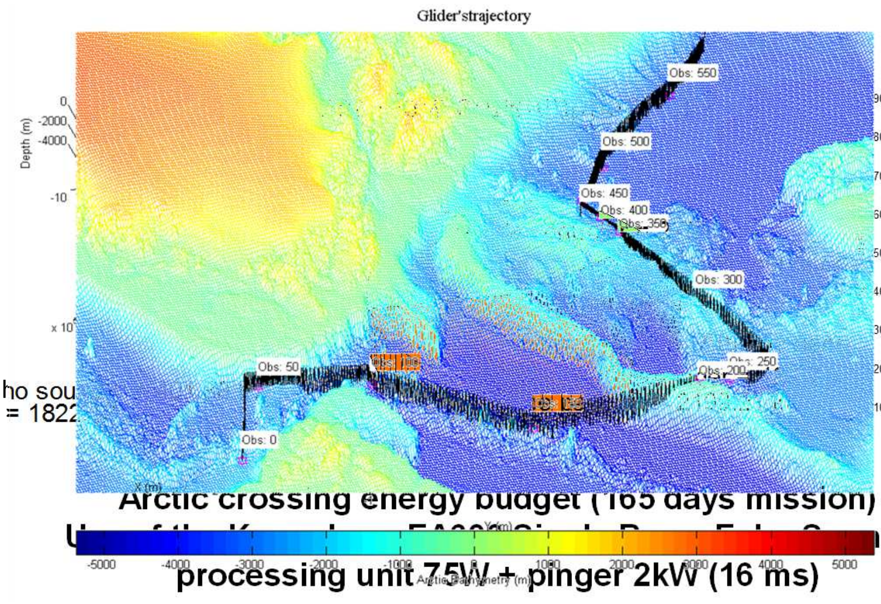
mission endurance ↔ capacity and usage of batteries

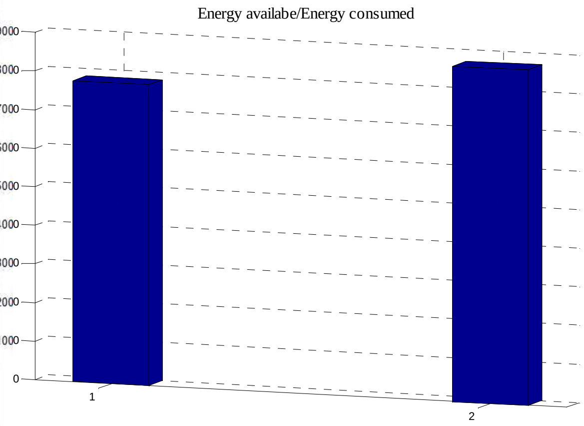
Terrain Based Navigation: a perfect low energy consumption navigation solution

- Tracking process => possibility to plan the pinging policy
- Re-initialize the dead reckoning process

Energy consumed repartition

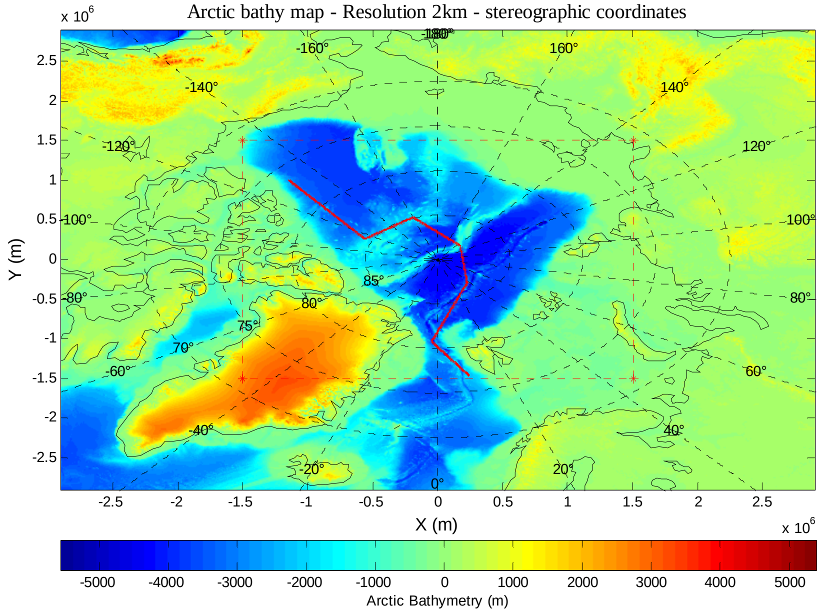






5. Energy Budget: Integrated Navigation System

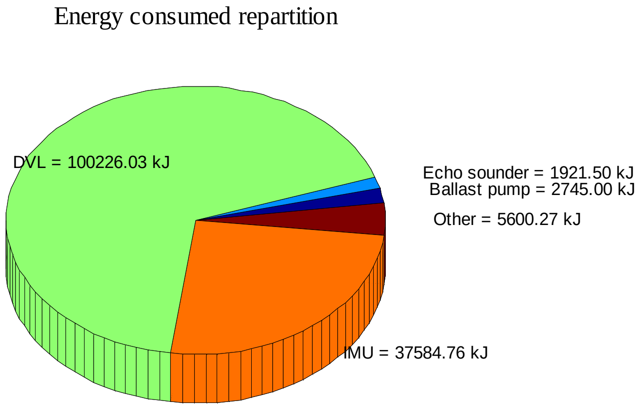
- Energy consumption of an inertial navigation system: 158 days simulation

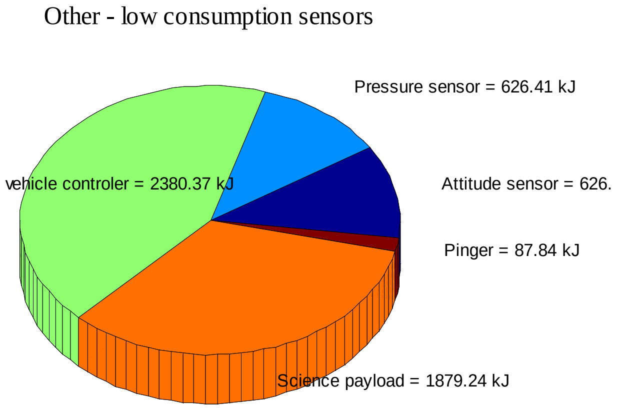


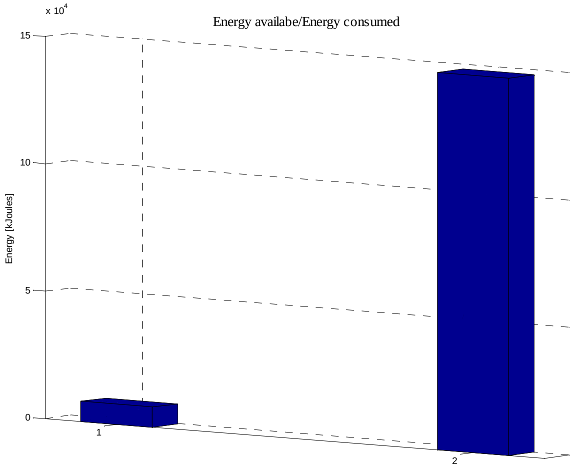
- - IMU Kongsberg MRU-Z: consumption 3 Watts
- - DVL RDI workhorse Navigator: consumption 8 Watts

the use of an Inertial Navigation System remains very “expensive”: 160 MJoules
= some 37 days of laptop energy requirements

=> glider’s battery (7800 KJoules) would be able to provide 1.5 day of laptop autonomy

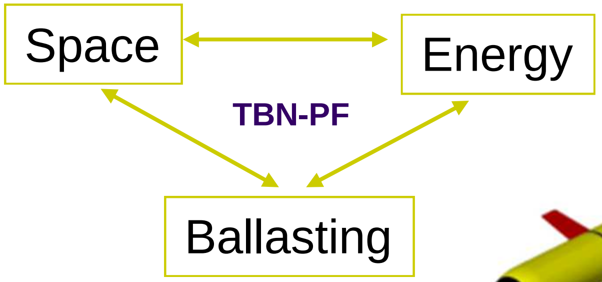


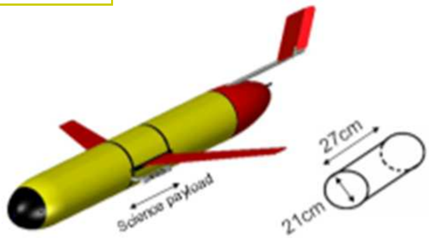


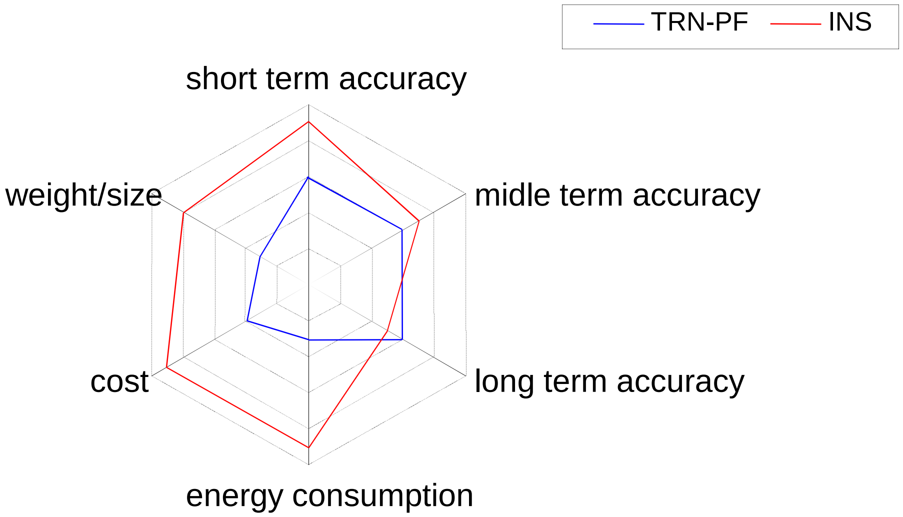


Conclusion

1. an accurate, precise and independent positioning estimation process
2. a limited endurance
3. a low cost technology


Space
Energy
TBN-PF
Ballasting




TRN-PF / INS qualitative comparison

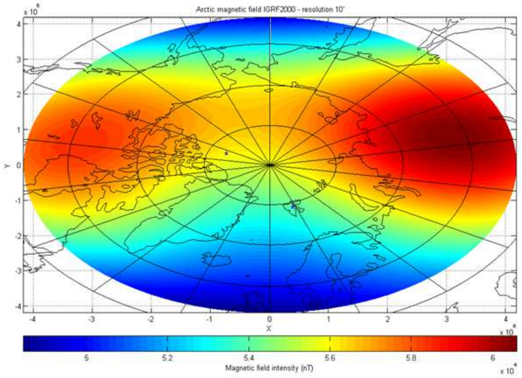
Outcome

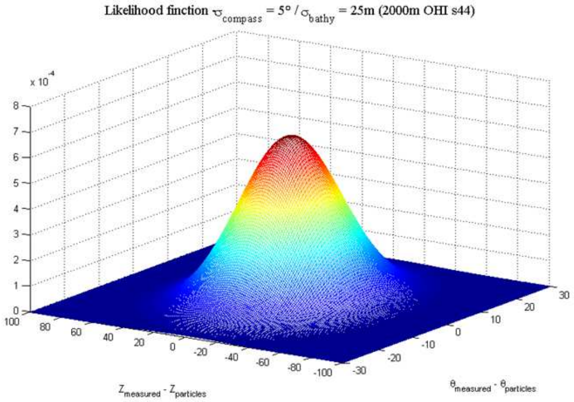
The TBN-PF is:
- a promising independent navigation estimation process for a long range under ice mission

However:
- the bathymetric data collected must be accurate
- a classical glider has not been able to load a low frequency single beam transducer

Perspectives

- Implementation of a 3D dynamic model
- Develop the energy budget study: processing energy consumption

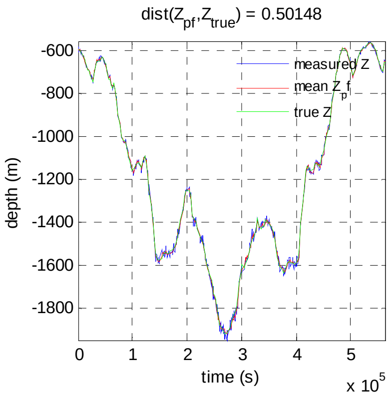


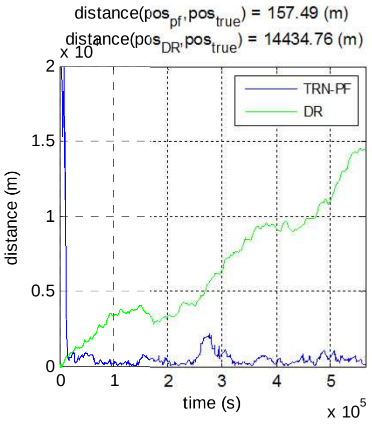


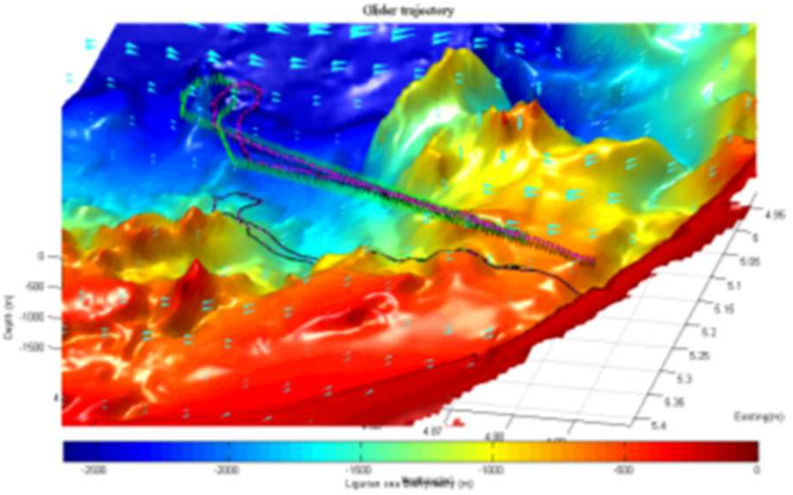
- Incorporate data from magnetometer in the navigation process (update step)

$$like = \frac{1}{\sqrt{2\pi}.\sigma_{bathy}}.e^{\frac{-(Z-Zi)^2}{2.\sigma^2_{bathy}}} \frac{1}{\sqrt{2\pi}.\sigma_{compass}}.e^{\frac{-(\theta-\theta i)^2}{2.\sigma^2_{compass}}}$$

- Test the Terrain Based Navigation in Ligurian Sea







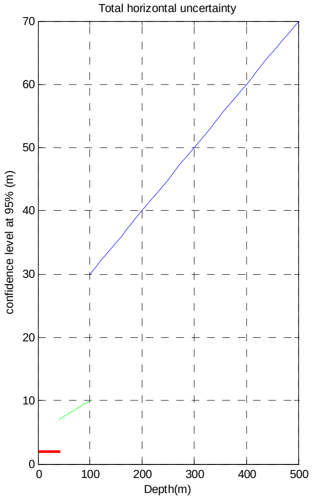
Back up slides

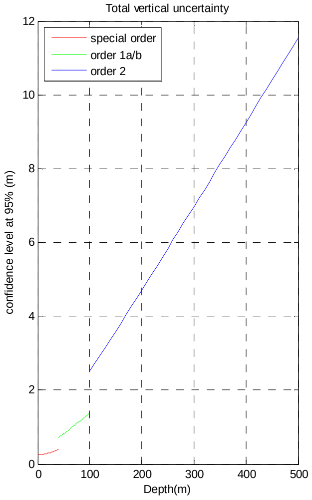
ENSIETA
ÉCOLE NATIONALE SUPÉRIEURE D'INGÉNIEURS

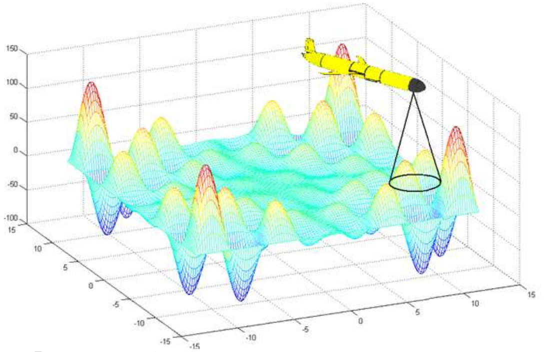
4. TBN – Particle Filter: Depth measurement uncertainty σ_{bathy}

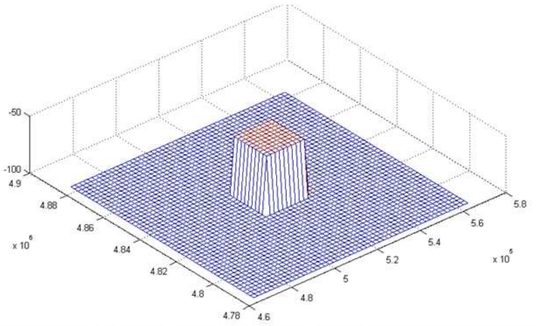
NURC
PARTNERING FOR MARITIME INNOVATION

- International Hydrographic organization (IHO) – S44

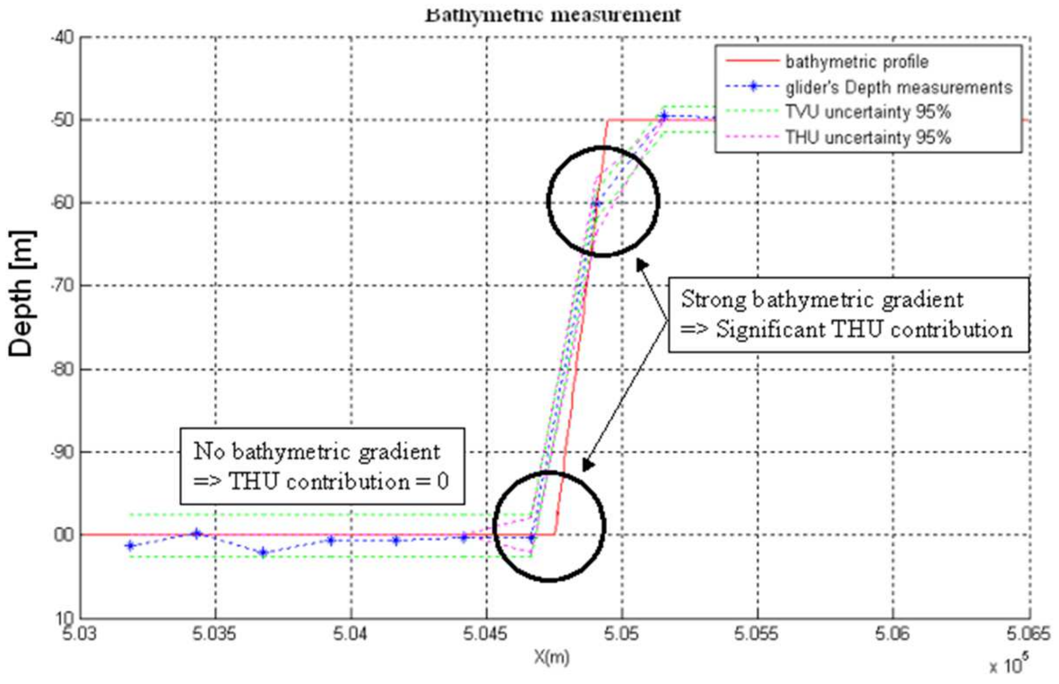


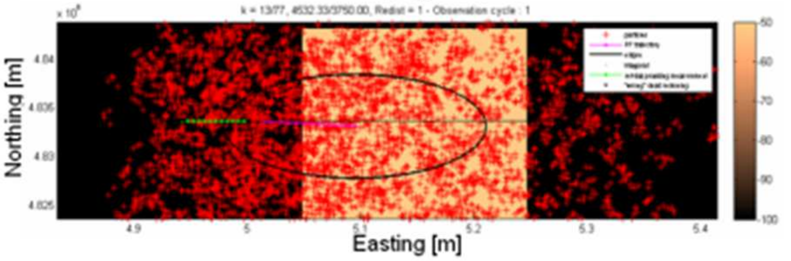


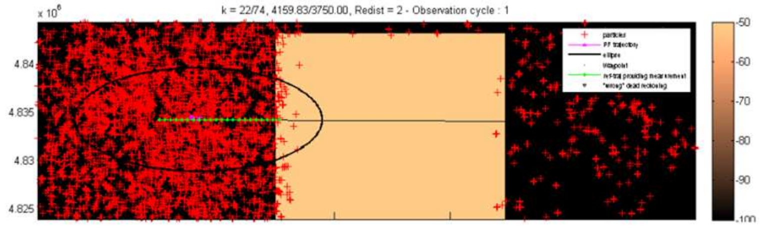


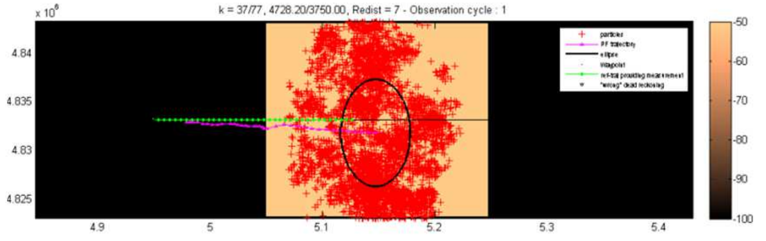


$$\sigma_{bathy} = \max(\sigma_{bathyTVU}, \sigma_{bathyTHU} .gradient_{map})$$



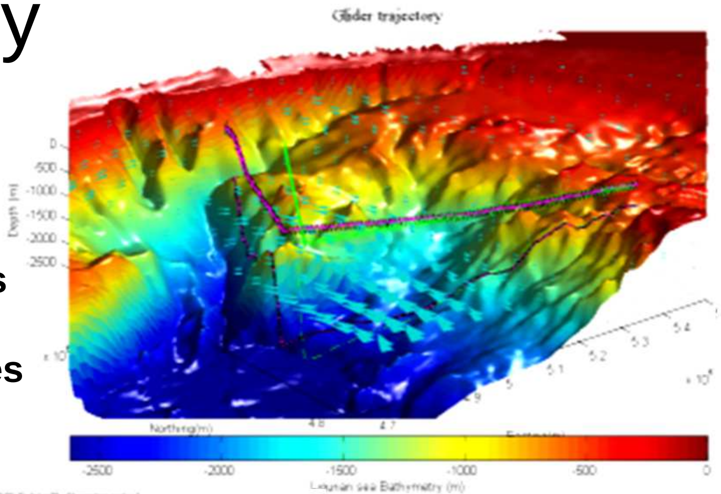




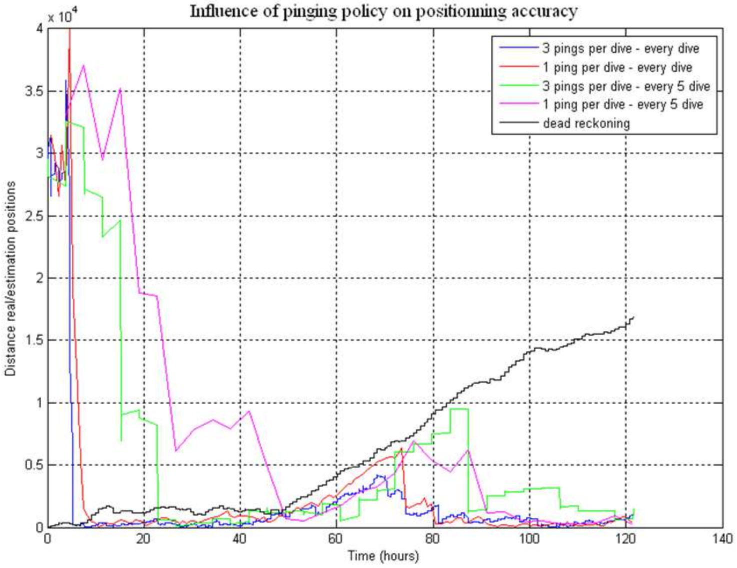


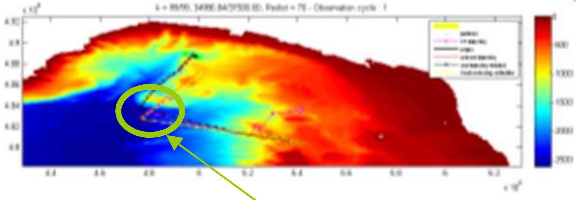
6. Simulations

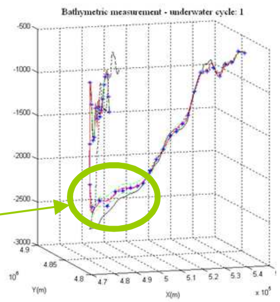
- Influence of pinging policy on positioning accuracy



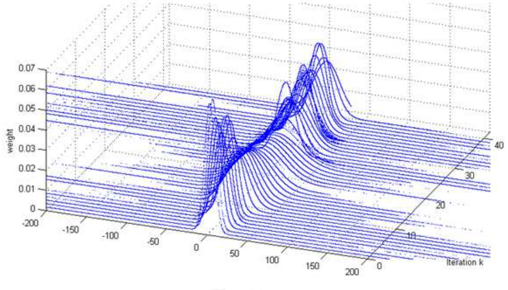
- **broadcasting a ping requires energy (32 Joules)**
- **different simulations with different broadcasting policies have been run**







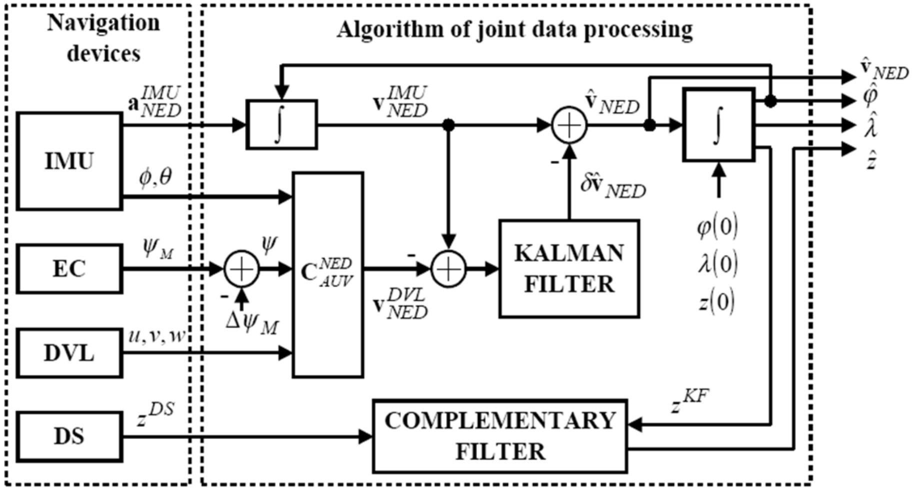
High uncertainty on depth measurement
=> Higher confidence given to dead reckoning



Simulation #	Pinging policy	Time needed to "converge"	Number of pings until convergence	Mean distance to real position	Standard deviation distance to real position
simulation 1	3 pings / every dive	5 hours	21	892 m	968 m
simulation 2	1 ping / every dive	10 hours	14	1185 m	1474 m
simulation 3	3 pings / every 5 dive	23 hours	21	2425 m	2344 m
simulation 4	1 ping / every 5 dive	48 hours	13	2076 m	2150 m

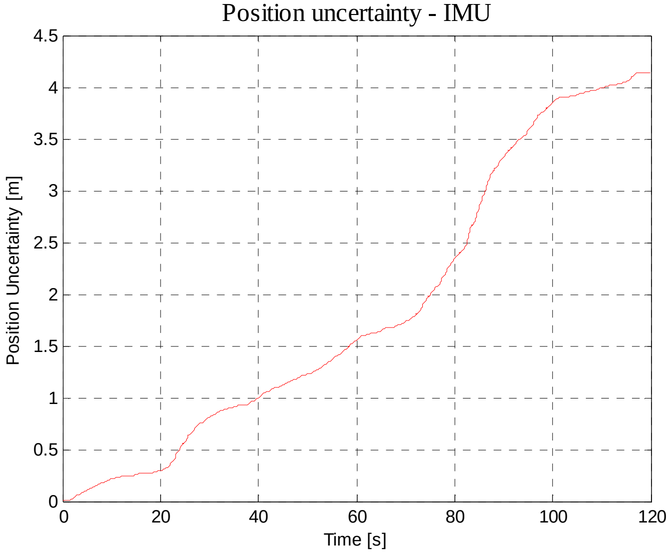
- **Low confidence on depth measurements => more significant weight given to the dead reckoning**

6. Simulations: comparison TBN-PF / Inertial Navigation System



- Inertial Navigation System

- Inertial Measurement Unit

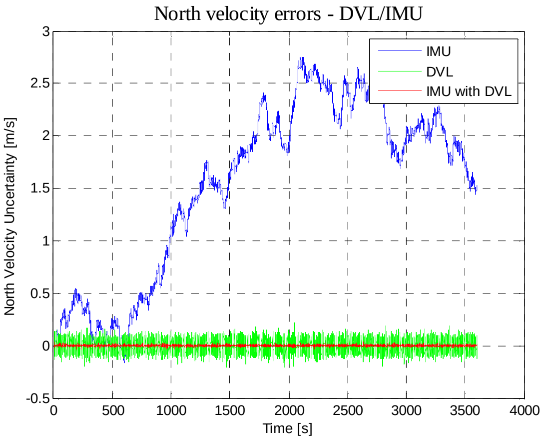


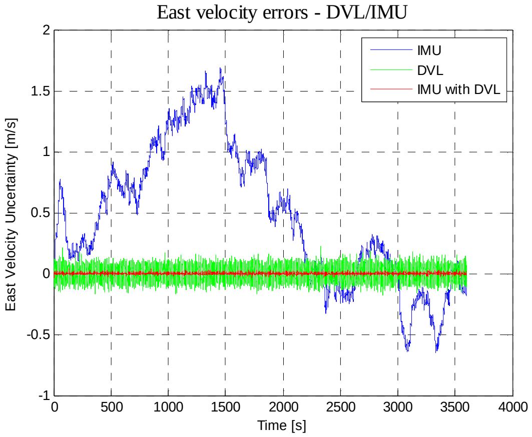
IXSEA ROVINS positioning performance:
No aiding for 1 min/2 min => 1.5 m/6 m

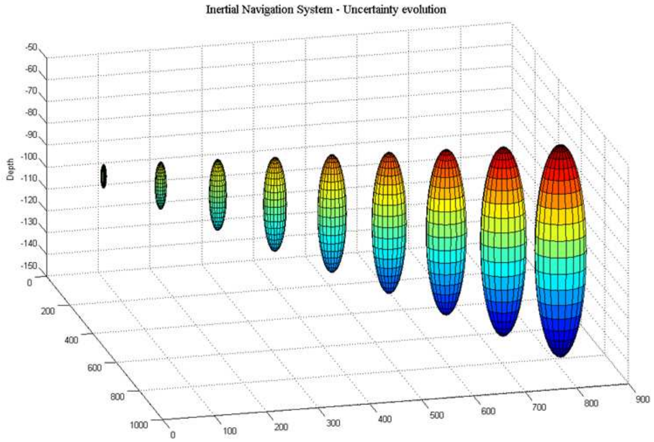
$$\sigma_{velocity}(k)=\sigma_{velocity}(k-1)+\sigma_{acceleration}\Delta T$$

$$\sigma_{position}(k)=\sigma_{position}(k-1)+\sigma_{velocity}(k-1)\Delta T$$

- Doppler Velocity Log aided Inertial Measurement Unit







uncertainty ellipsoid growth
5 hours simulation at a 5Hz sampling