# Underwater Glider Path Planning and Population Reduction in Differential Evolution

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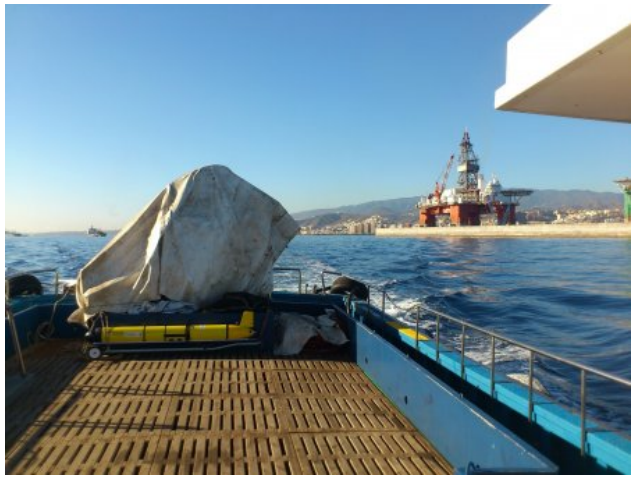
# Introduction

- 1) Underwater glider, mesoscale eddies
- 2) Path planning (ocean trajectory), trajectory test scenarios
- 3) Evolutionary optimization, differential evolution
  - improvement mechanism for trajectory optimization:
  - population size reduction in differential evolution.
- 4) Experiments, results

# Robotic unmanned sea glider Slocum G2

- High durability: 25 to 365 days,
- long range 600–1500 km (alk. batt.), 4000–6000 km ($Li^+$)
  - buoyancy-driven: horizontal 0.35m/s (0.68 knots),
  - 2 knots using propeller.
- Dive to depth 1000 meters, long range, modular,
- integrates sensors of physical and bio/chemical parameters[2]
  - temperature, salinity, dissolved oxygen, turbidity, chlorophyl and sea currents - possible rapid replacement of sensors.





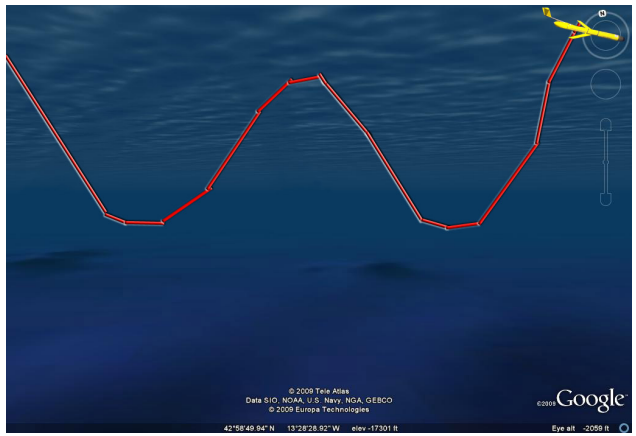
[1] lh6.googleusercontent.com/-Mq308aI1s2g/UHVf4k3uoiI/AAAAAAAACbw/LeiYHXMQRbs/s640/PA060013.JPG

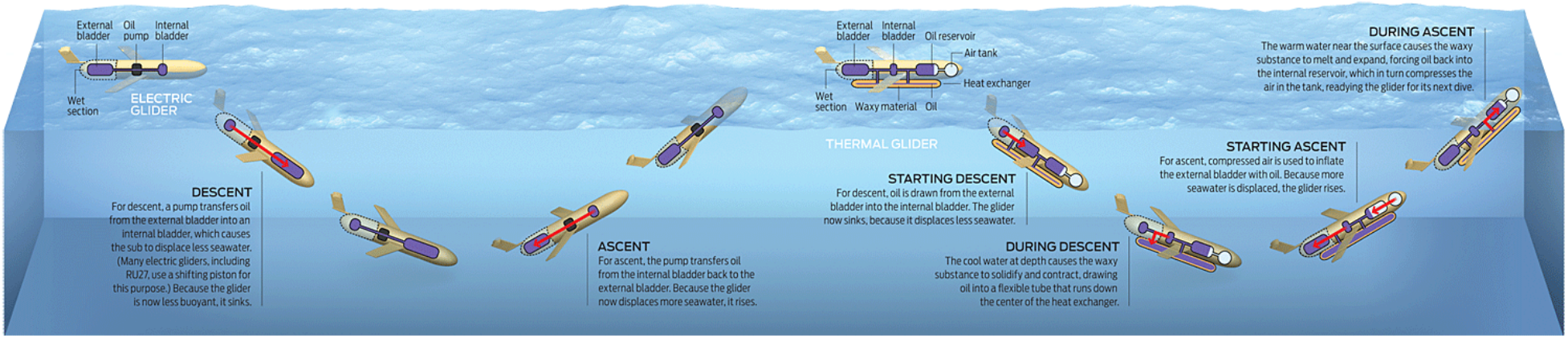
[2] http://www.webbresearch.com/pdf/Slocum_Glider_Data_Sheet.pdf

# The buoyancy drive and submarine probes usefulness

- Driving "yoyo" uses little energy, descent and rise (pump); also for maintaining direction little power is consumed.

+ Use: improving ocean models with real data,
+ the real data at the point of capture,
+ sampling flow of oil discharges,
+ monitoring cable lines, and
+ real-time monitoring of different sensor data.

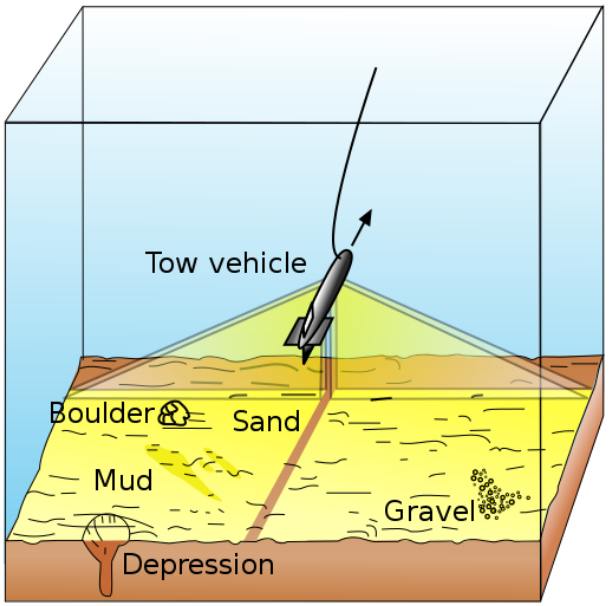


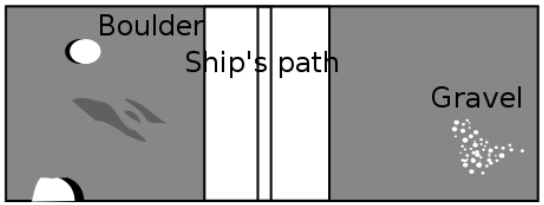



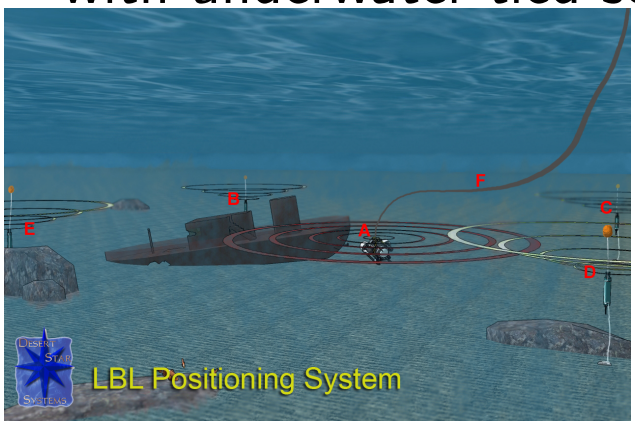

[1] http://www.i-cool.org/wp-content/uploads/2009/11/google-earth-glider-path.jpg
[2] http://spectrum.ieee.org/image/1523708

# Satellite navigation and autonomy

- Radio waves can not penetrate deep water, GPS signal is cut.
  - During a dive the AUV is autonomous,
  - AUV uses internal sensors for navigation,
    - compass, depth, sonar, relief sonar (mapping seabed[1]), gyroscope, accelerometer, magnetometer, thermistor, conductivity meter.
  - acoustic modem for wireless communication with underwater tied sensors[2].



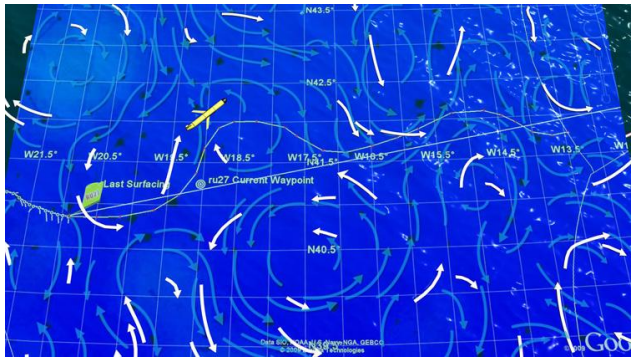



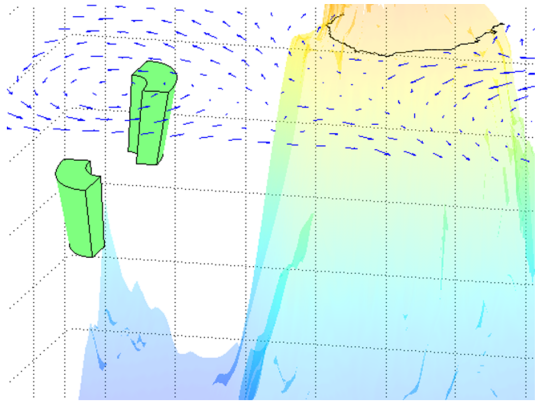




[1] http://upload.wikimedia.org/wikipedia/commons/5/5b/Side-scan_sonar.svg
[2] http://upload.wikimedia.org/wikipedia/commons/a/ad/LBL_Acoustic_Positioning_Aquamap_ROV.jpg
[3] http://www.ego-network.org/dokuwiki/lib/exe/fetch.php?media=img:glider3.gif

# Real-time data streams on the environment

- MyOcean IBI (`http://myodata.puertos.es/`),
- different satellite data about the sea (eg. currents),
- *Regional Ocean Modelling System*: refreshment each 4 hours,
- covers 19° W 5° / E 26° N 56° N, resolution 1/36°,
- furthermore: a surrogate currents model in 3D,
  - extrapolation from 2D surface data (3 days each 4 hours),
  - computed using 3D interpolation from neighboring points.



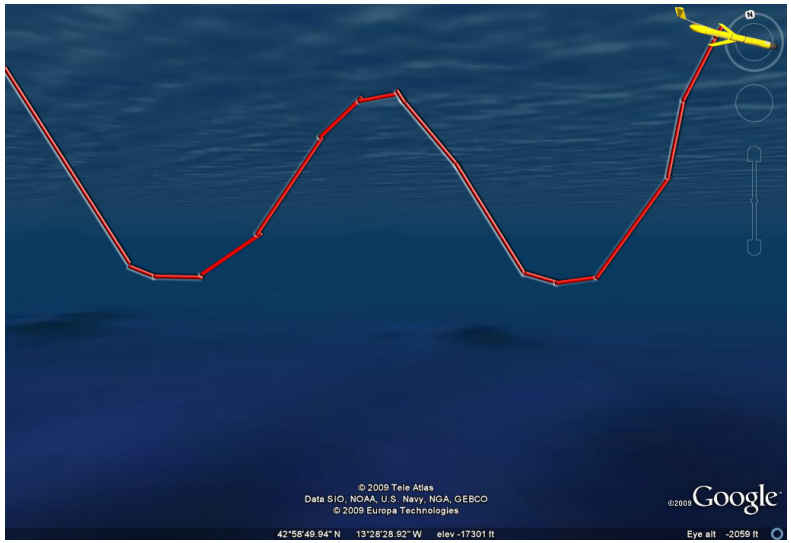
[1] `http://ocean.si.edu/sites/default/files/styles/colorbox_full/public/photos/glider_RU27_eddies_extra%20arrows.jpg?itok=pqbU1Vba`

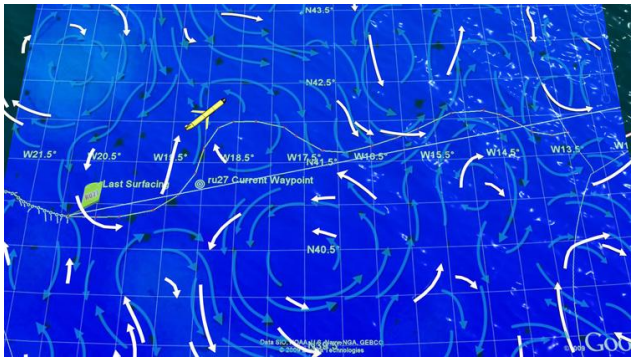
[2] `http://robotics.usc.edu/~ryan/Publications_files/GliderEddyPlan.pdf`

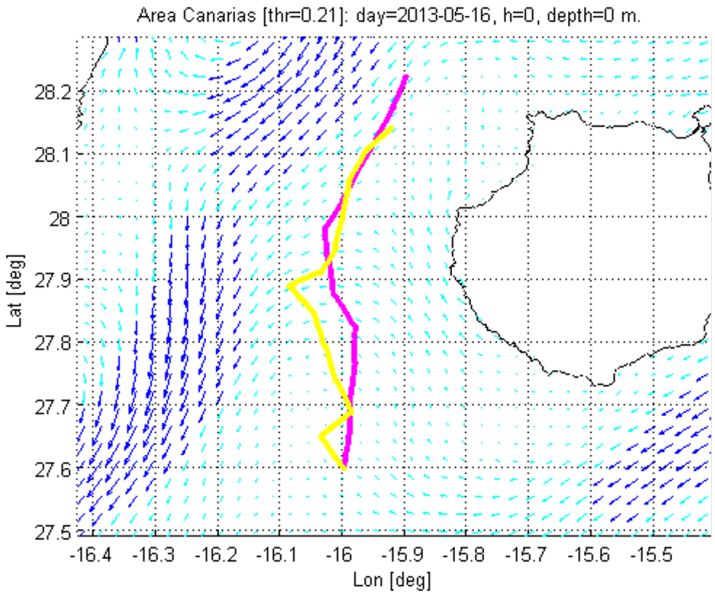
# The optimal trajectory task

fitness evaluation (UGPP simulation):

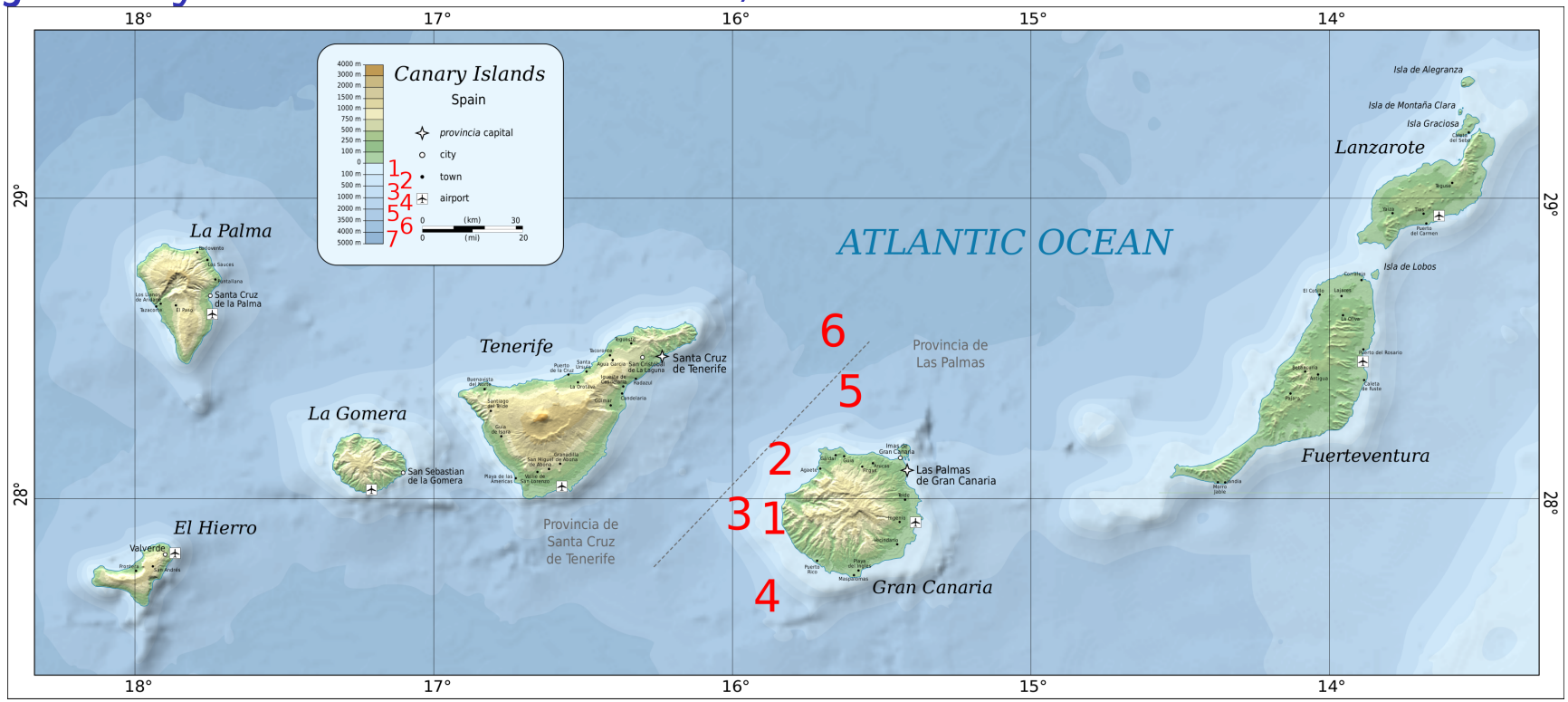
$b_0 = \text{bearing}(\mathbf{p}_0, \mathbf{p}_{\text{target}})$;
$b_1 = b_0 + u_{i,1,g+1}$;
$\mathbf{p}_1 = \text{simulate_stint}(\mathbf{p}_0, b_1, \text{map})$;
**for** $j = \{2, 3, ..., D\}$:
$b_j = b_{j-1} + u_{i,j,g}$;
$\mathbf{p}'_{j-1} = \text{simulate_drift}(\mathbf{p}_{j-1}, \text{map})$;
$\{\mathbf{p}_j\} = \{\mathbf{p}_{j-1}\} \cup \text{simulate_stint}(\mathbf{p}'_{j-1}, b_j, \text{map})$;
**end for**
$f(\mathbf{u}_{i,g}) = \| \mathbf{p}_D - \mathbf{p}_{\text{target}} \|$;



# Trajectory scenarios – *ocean, mesoscale eddies*









Images: Wikipedia, Google Earth

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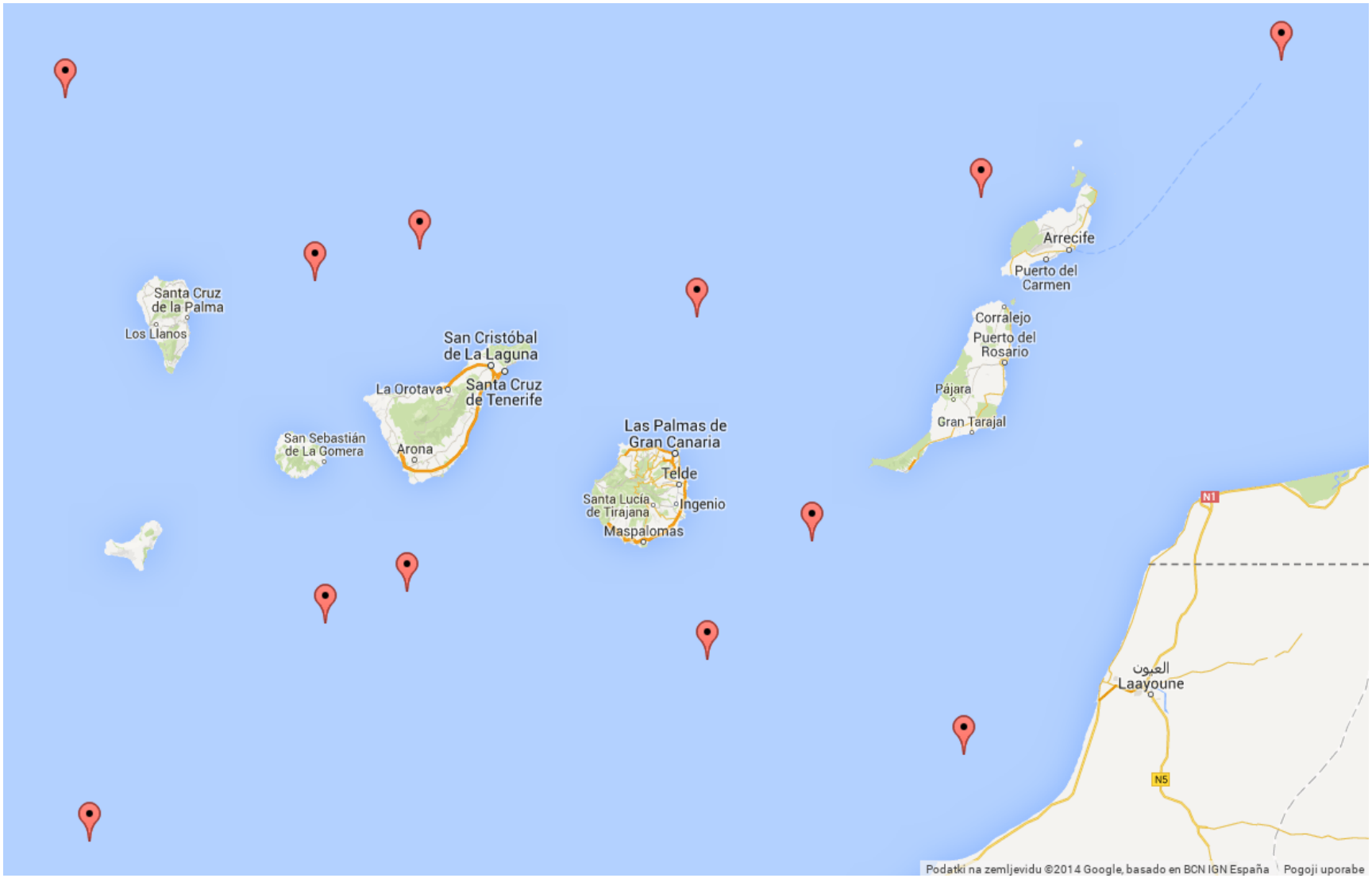
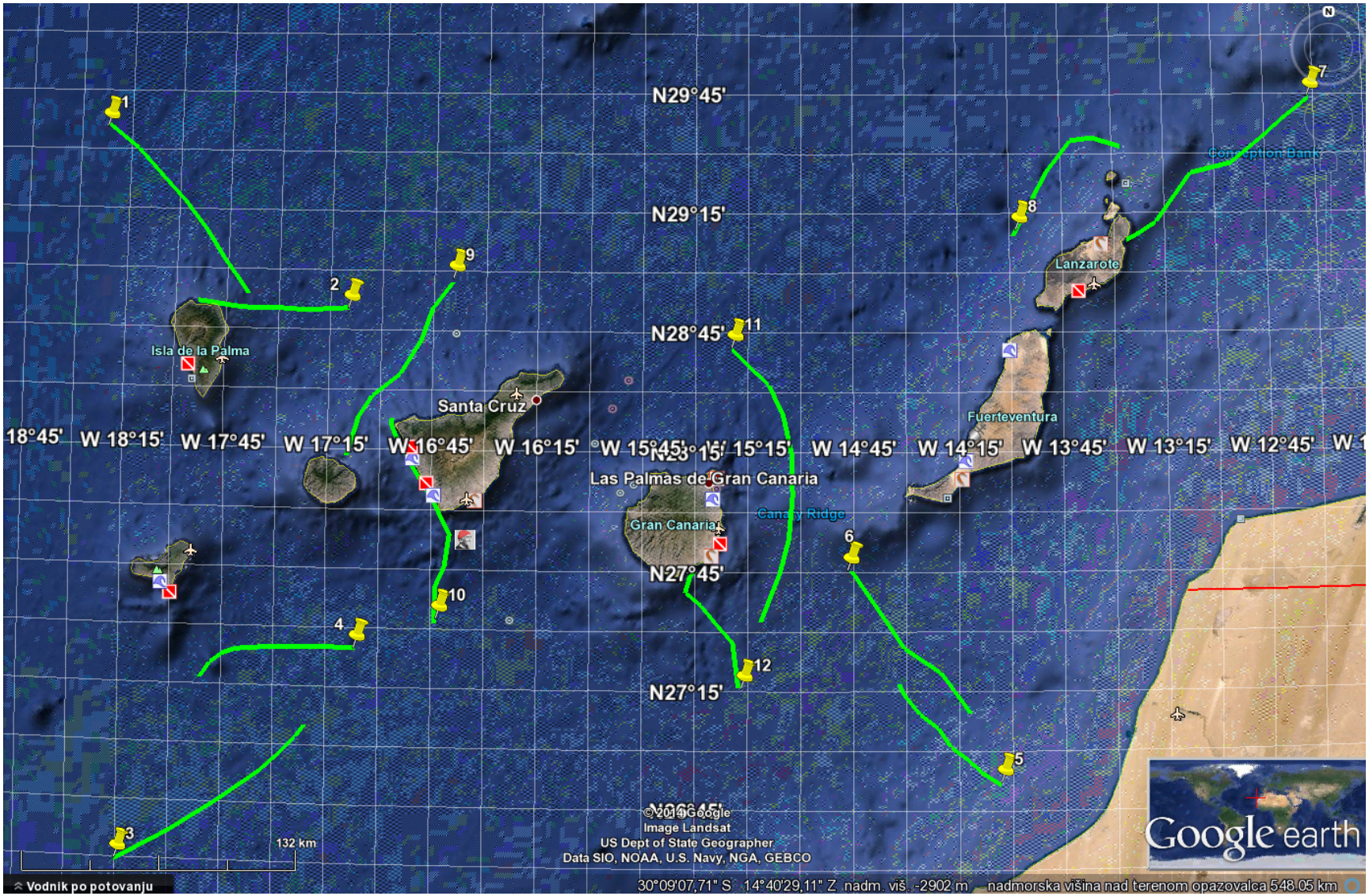
# Trajectory scenarios – *simulation points*



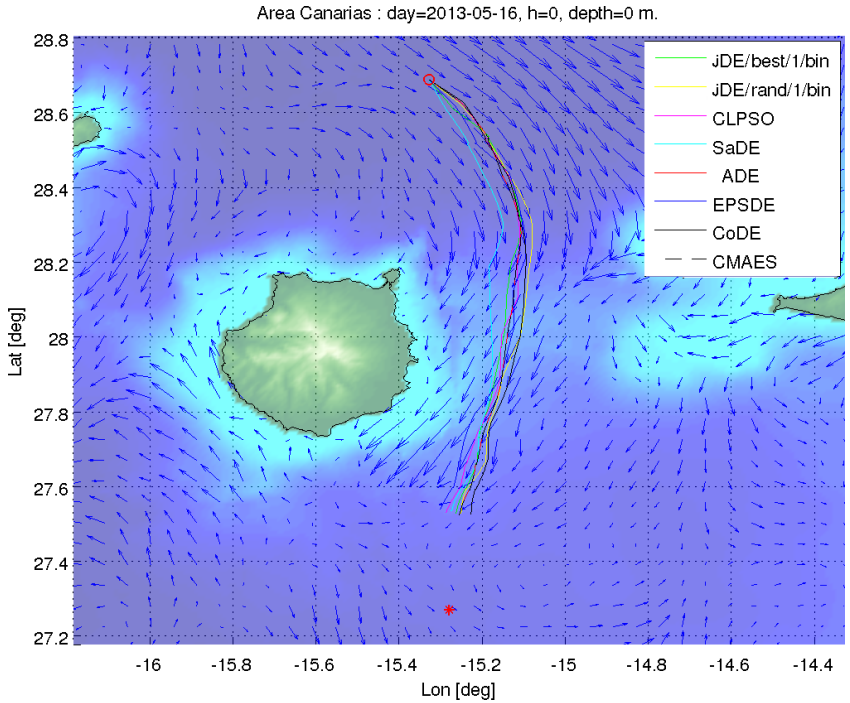

http://www.darrinward.com/lat-long/?id=379544

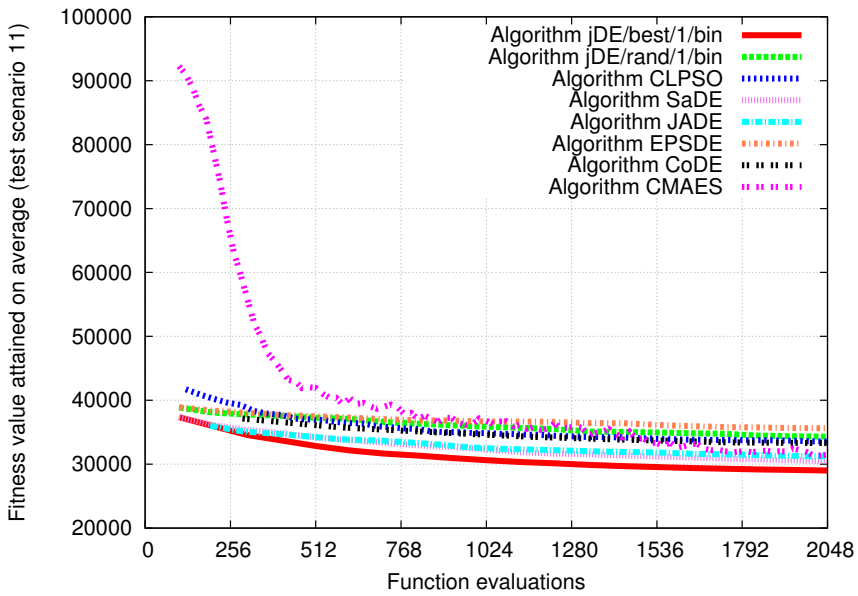
# Trajectory scenarios – *path planning optimization*




https://www.google.si/maps/@28.059806,-15.998355,650054m/data=!3m1!1e3

# Example trajectories optimization – scenario 11




Zamuda, J. D. Hernández Sosa. Differential Evolution and Underwater Glider Path Planning Applied to the Short-Term Opportunistic Sampling of Dynamic Mesoscale Ocean Structures. *Applied Soft Computing*, November 2014, vol. 24, pp. 95–108.

# Optimization algorithms

- Computing Machines + Intelligence = Artificial Intelligence
- Computational Intelligence
- Global Optimization

$$f'(x) = \frac{\Delta f(x)}{\Delta x}, \quad f^*(x) = f(x) + \Delta x f'(x).$$

- Mathematical Programming
- Evolutionary Computation
- **Evolutionary Algorithms** (EA)
  - population-based
  - mutation, crossover, selection

# Differential Evolution (DE) – small, versatile EA optimizer

- A floating point encoding EA for global optimization over continuous spaces,
  - through **generations**,
    **the evolution process** improves **population of vectors**,
  - iteratively by combining a parent individual and several other individuals of the same population.
- We choose the **strategy** *jDE/rand/1/bin*
  - **mutation**: $\mathbf{v}_{i,G+1} = \mathbf{x}_{r_1,G} + F \times (\mathbf{x}_{r_2,G} - \mathbf{x}_{r_3,G})$,
  - **crossover**:
    $$u_{i,j,G+1} = \begin{cases} v_{i,j,G+1} & \text{if } \mathrm{rand}(0,1) \leq CR \text{ or } j = j_{rand} \\ x_{i,j,G} & \text{otherwise} \end{cases},$$
  - **selection**: $\mathbf{x}_{i,G+1} = \begin{cases} \mathbf{u}_{i,G+1} & \text{if } f(\mathbf{u}_{i,G+1}) < f(\mathbf{x}_{i,G}) \\ \mathbf{x}_{i,G} & \text{otherwise} \end{cases},$
  - includes mechanism of $F$ and $CR$ control parameters self-adaptation.

# A DE algorithm extension: population size reduction

- Reducing population size by half (dynNP-DE),

$$G_p > \frac{N_{max_Feval}}{p_{max} NP_p},$$

  - when number of generations exceeds ratio between the number of function evaluations allowed and the population size.
  - Two parameters:
    - initial population size ($NP_{init}$) and
    - number of population reductions ($pmax$).
- Other extensions (unused here) of the original jDE algorithm:
  - multi-objective optimization,
  - SQP local search,
  - $\epsilon$-constraint handling,
  - three random strategy usage,
  - ageing of vectors, and
  - mutation rate $F$ sign changing,
  - multiple strategies.

# Some other instances of evolutionary algorithms

- CLPSO - a Particle Swarm Optimization algorithm,
- CMAES - an Evolutionary Strategy algorithm, Eigen-matrix,

- (jDE) - the Differential Evolution (DE) algorithm @ UM,
- SaDE - DE algorithm (NTU),
- JADE - DE (more greedy than basic jDE),
- EPSDE - DE (parameterization),
- CoDE - DE (parameterization).

- A comprehensive performance comparison published in:

  A. Zamuda, J. D. Hernández Sosa. Differential Evolution and Underwater Glider Path Planning Applied to the Short-Term Opportunistic Sampling of Dynamic Mesoscale Ocean Structures. *Applied Soft Computing*, November 2014, vol. 24, pp. 95–108.

# A new experimental setup and hypothesis

- Two new types of DE strategies (`DE/best` and `DE/rand`)
  - applied to underwater glider path planning (UGPP)
- The newly proposed DE instance algorithms
  - population size reduction on the `best` and `rand` DE strategies
  - assessed and compared on the 12 test scenarios.
- A Bonferroni-Dunns statistical hypothesis testing
  - to confirm outperformance of the favorized `DE/best` strategy
  - over the `DE/rand` strategy for the 12 UGGP scenarios utilized.

- The analysis suggests the approach can benefit from:
  - gradually reducing the population size and
  - also tuning the DE parameters.

# The code

**Algorithm :** Differential evolution for underwater glider path planning

**procedure** jDE_UGPP($\mathbf{x}^*$)
**Require:** $\mathbf{p}_0$ (current glider location), map (MyOcean IBI), $\mathbf{p}_{\text{target}}$ (mission target point), $MAX_FES$ (maximum number of FES allocated), $NP$ (DE population size), $F_l$, $F_u$, $\tau_1$, and $\tau_2$ (jDE constants)
**Ensure:** **x** – list of instructions on how to navigate glider
`uniform randomly generate DE initial population` $\mathbf{x}_{i,0}, \forall i \in \{1..NP\}$;
**for** DE generation loop $g$ (while FES <$MAX_FES$)**do**
**for** DE iteration loop $i$ (for all individuals $\mathbf{x}_{i,g}$ of a population) **do**
**DE population reduction;**
DE individual $\mathbf{x}_{i,g}$ computation (adaptation, mutation, crossover):

$$F_{i,g+1} = \begin{cases} F_l + rand_1 \times F_u & \text{if } rand_2 < \tau_1, \\ F_{i,g} & \text{otherwise} \end{cases};$$

$$CR_{i,g+1} = \begin{cases} rand_3 & \text{if } rand_4 < \tau_2, \\ CR_{i,g} & \text{otherwise} \end{cases};$$

$$\mathbf{v}_{i,g+1} = \mathbf{x}_{r_1,g} + F_{i,g+1}(\mathbf{x}_{r_2,g} - \mathbf{x}_{r_3,g});$$

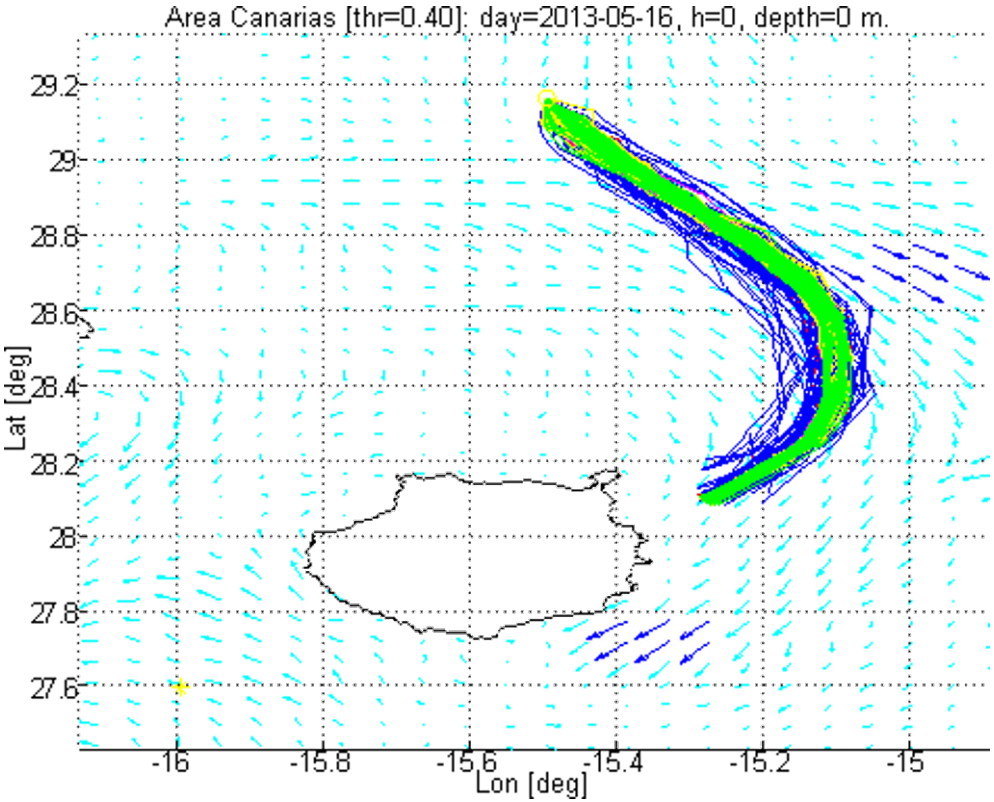
$$u_{i,j,g+1} = \begin{cases} v_{i,j,g+1} & \text{if} rand(0,1) \leq CR_{i,g+1} \text{or} j = j_{rand} \\ x_{i,j,g} & \text{otherwise} \end{cases}, \quad \forall \ j \in \{1, \ldots, D\};$$

DE fitness evaluation (UGPP simulation):
$b_0 = \text{bearing}(\mathbf{p}_0, \mathbf{p}_{\text{target}})$;
$b_1 = b_0 + u_{i,1,g+1}$;
$\mathbf{p}_1 = \text{simulate_stint}(\mathbf{p}_0, b_1, \text{map})$;
**for** $j = \{2, 3, \ldots, D\}$:
$b_j = b_{j-1} + u_{i,j,g}$;
$\mathbf{p}'_{j-1} = \text{simulate_drift}(\mathbf{p}_{j-1}, \text{map})$;
$\{\mathbf{p}_j\} = \{\mathbf{p}_{j-1}\} \cup \text{simulate_stint}(\mathbf{p}'_{j-1}, b_j, \text{map})$;
**end for**
$f(\mathbf{u}_{i,g}) = ||\mathbf{p}_D - \mathbf{p}_{\text{target}}||$;
DE selection:

$$\mathbf{x}_{i,g+1} = \begin{cases} \mathbf{u}_{i,g+1} & \text{if} f(\mathbf{u}_{i,g+1}) < f(\mathbf{x}_{i,g}) \\ \mathbf{x}_{i,g} & \text{otherwise} \end{cases};$$

**end for**
**end for**
**return** the best individual obtained among $\mathbf{x}_{i,G}$;

# Results – phenotype paths obtained using DE/best

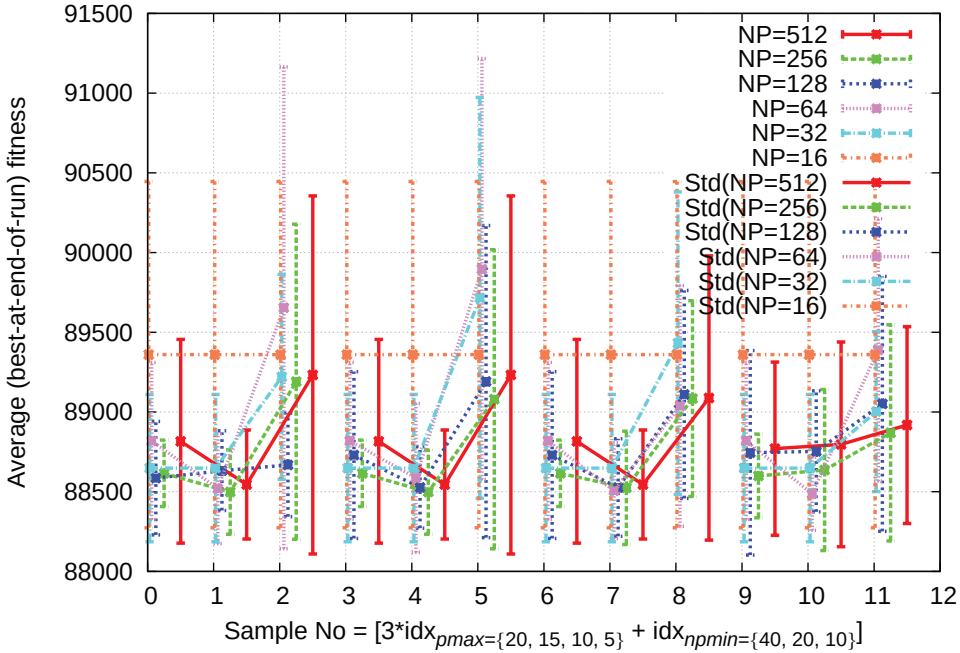



- Trajectory simulations:
  - 12 bearings
  - computed with best taking population size ($NP$) as the study factor.

- $NP$ values: 8 (blue), 32 (purple), 128 (yellow), 512 (green)

- 120 runs subsampled with step 10
  - one run drawn per $NP$, resulting in 12 trajectories shown.

# Results – phenotype paths obtained using DE/best




- Different population sizing settings
- aggregated on 10 independent runs,
- impact on mean final fitness value for different
  - minimal $NP$ ($NP_{\min}$) and
  - number of reductions ($pmax$).

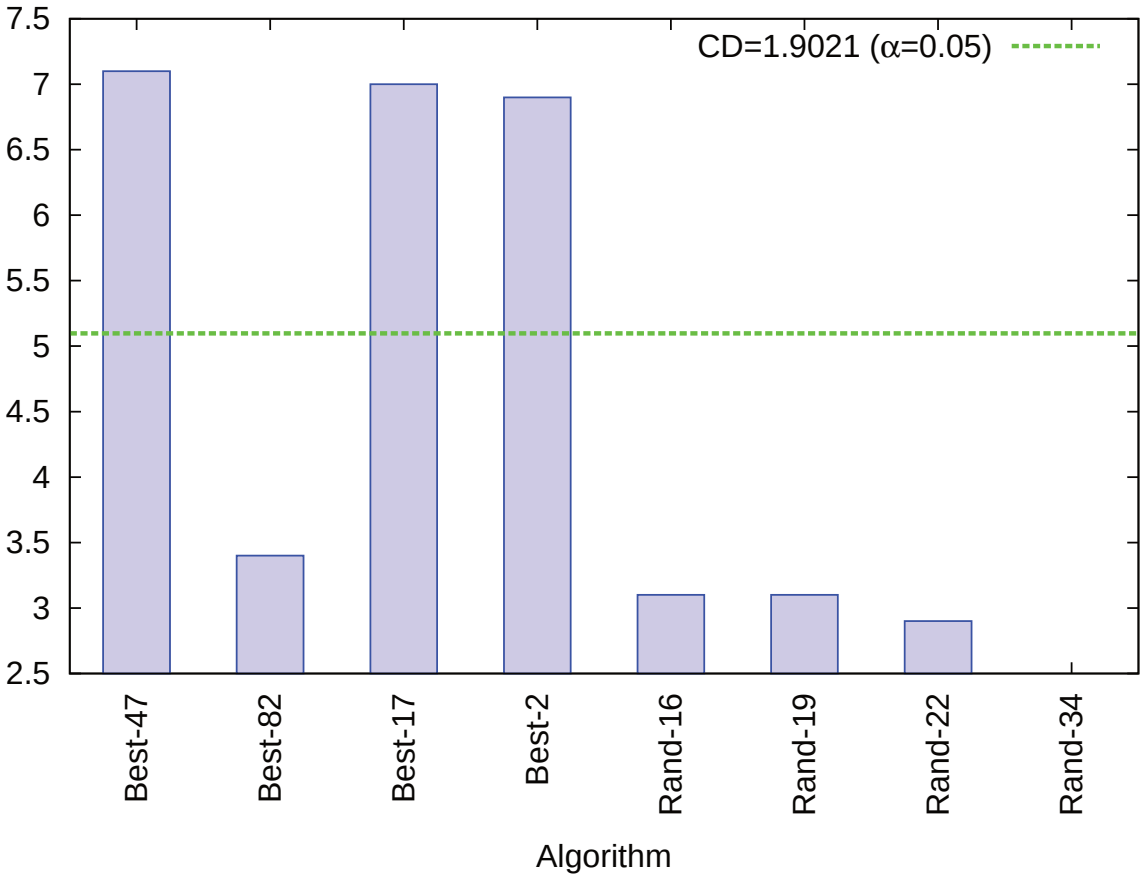
- Drawn are also standard deviation values of the means.

- Best results: DE/best with $NP$=64, $pmax$=5, $NP_{\min}$=20.

# Results – comparing selected optimization algorithms

Bonferroni-Dunn test on UGPP

- control algorithm: `DE/best` with $NP$=64, $pmax$=5, $NP_{\min}$=20,
- 51runs, 12scenarios, MAXFES 2048.




The control algorithm outperforms some `DE/best` and all `DE/rand` variants.

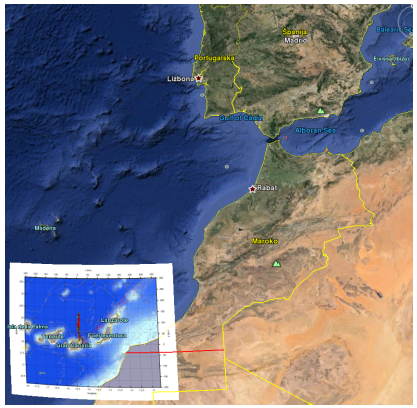
# Summary

- Underwater glider, satelite navigation and autonomy,
- real-time data streams about the environment,
- challenge of short-time mesoscale eddies on GC islands,
- the task of optimal trajectory, optimization algorithms, DE,
- example approach, real mission results, p201,ESTOC2013_3,
- differential evolution,
- mechanism of using population size reduction,
- improved results on test scenarios.


- This work was partially funded by the
  - Slovenian Research Agency, project P2-0041 and
  - Canary Island government and FEDER funds, project 2010/62.

# Thank you very much for listening!




Thanks to the organisers of the Eurocast 2015 conference.

# Questions and suggestions?