Cooperative distributed localization and environmental sampling by AUV teams

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Menu

- AUVs for environmental sampling
  - *gliders*
  - *propelled*
  - *hybrid*
- Adaptive sampling and autonomy
  - *data-driven vs. model-driven*
- Networking and cooperation
- Limitations to uw robot team cooperation
  - *communication*
  - *localization*
- Adaptive sampling in a communication constrained environment

AUVs for environmental sampling

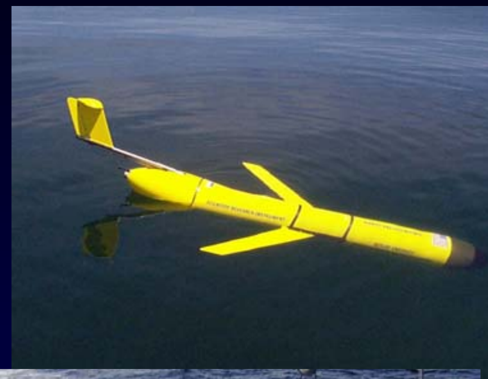
- **Traditional measurements in a cost-effective way**:
  - replace ship and/or buoys with autonomous vehicles
  - pre-program the mission, receive data at a remote station
  - CTDs, water quality, bathymetry, seabed morphology
  - *data quality enhanced by the use of an underwater platform*

- **New measurements possibilities**
  - gradient-following, feature mapping, synoptic measurements
  - exploit the on-board intelligence as data are gathered: *adaptivity*
  - exploit the availability of multiple vehicles: *team cooperation*

Some AUVs …

Oceanographic gliders

very long endurance
inexpensive
oceanographic sampling
pre-programmed mission
cooperation (Leonard et al.)



Propelled AUVs

deep water

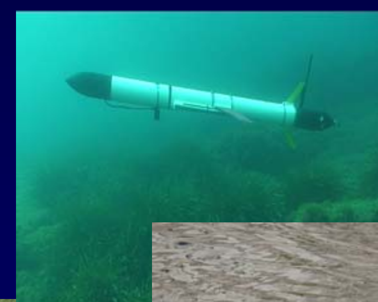
long endurance
very expensive
seabed mapping
pre-programmed mission

shallow water

some endurance
moderately expensive
oceanography, seabed mapping
pre-programmed, cooperation

”Hybrid” vehicles

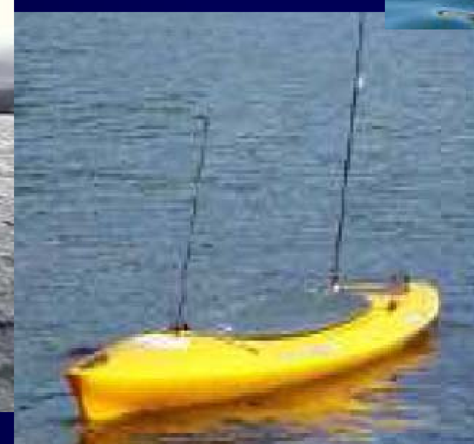
some endurance
inexpensive
oceanographic sampling
pre-programmed mission
cooperation



… and some ASV - Autonomous Surface Vehicles

OASIS (NOAA) - Delfim (IST)

Scout (MIT) - Charlie (CNR-ISSIA)



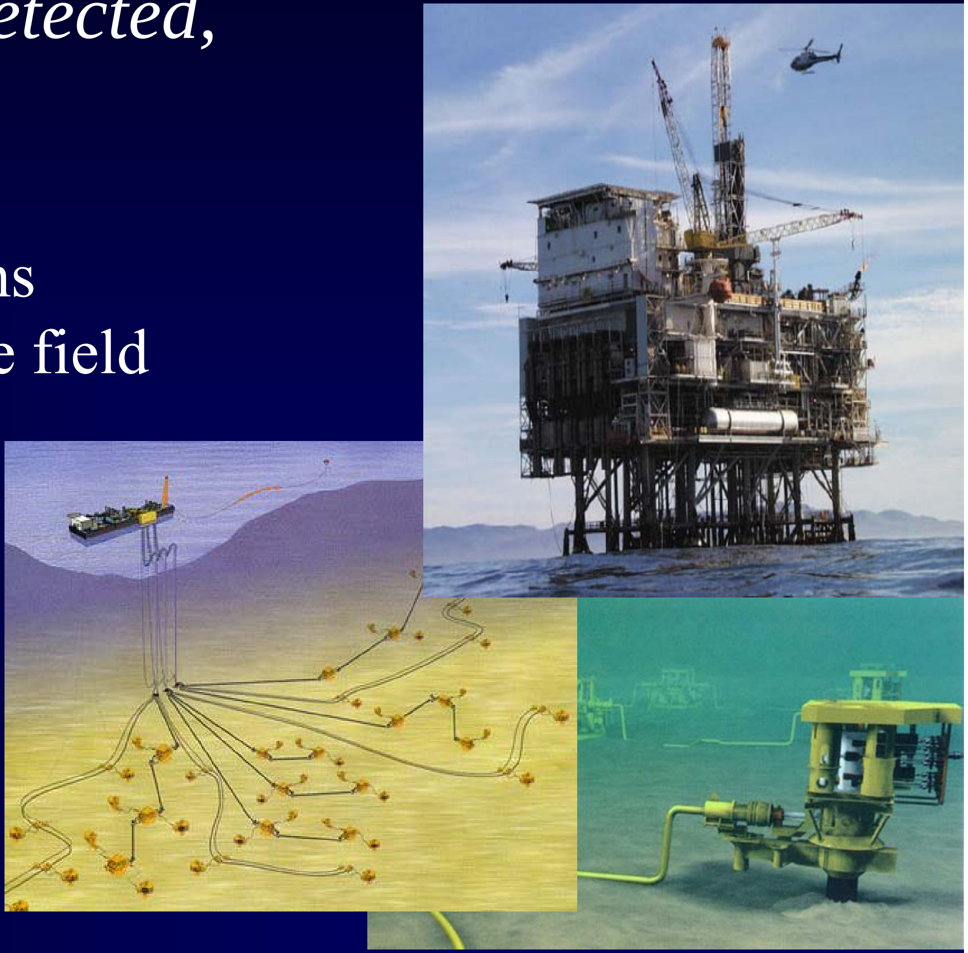
Adaptation and autonomy

- Sample at points/ paths that maximize some figure of merit related to our knowledge of the sampled field

- In the oceanographic context adaptation can be:
  - *Model driven:*
    - use model prediction to determine next <u>mission</u>
    - no autonomous planning needed (but autonomous navigation required)
    - *open loop - feedback*
  - *Data driven:*
    - use data to determine next <u>way-point</u>
    - autonomous planning as well as autonomous navigation
    - *feedback only*

Where/when is data driven adaptation needed?

- *Whenever occurrence of anomalous events has to be monitored, detected, classified*
- E.g.: gas&oil fields
  - Fixed sensors in key positions
  - Periodic sampling around the field
- Other instances:
  - water quality in touristic coastal areas
  - industry discharge
  - *security*: intrusion detection, mine/ordeal search



Some formal frameworks for data-driven adaptive sampling

- A clear qualitative concept
  - – increase sample density when the measured quantity is rapidly varying (either in time and/or in space)
  - – estimate variation rate from past or neighborhood data
- Sampling metric
  - – *deterministic setting*: smoothness
  - – *probabilistic setting*: information gain
  - – application-dependent weighing
  - – use tools from both approaches

Deterministic setting: smoothness

- A *measure* of the variability of the field
  - weighed sum of the time and spatial derivatives

$$\left\|F(\mathbf{r};t)\right\|_{S_n} = \sum_i^n b_{i,\mathbf{r}} \left\|D_{i,\mathbf{r}}F\right\| + c_{i,t}\left\|D_{i,t}F\right\|$$

$$\left\|F(\mathbf{r};t)\right\|_{S_n} \le k$$

  - projection over a space of basis functions, ordered with increasing variability

$$F(\mathbf{r};t) = \sum_i^{\infty} h_i \phi_i(\mathbf{r};t) \qquad h_i = \prec F;\phi_i \succ$$

$$\sqrt{\sum_{i=n}^{\infty} h_i^2} < k$$

- Adapt the sampling step to the *local* smoothness
- Estimate local smoothness from available data

Probabilistic setting: information gain

- Minimize the expected uncertainty of the field
  - *A priori* mean and covariance of the field

$$\bar{F}(\mathbf{r};t) = E\{F(\mathbf{r};t;\xi)\}$$

$$C(\mathbf{r},\mathbf{r}';t,t') = E\{[F(\mathbf{r};t) - \bar{F}(\mathbf{r};t)][F(\mathbf{r}';t') - \bar{F}(\mathbf{r}';t')]\}$$

  - *m* measurements at points ($\mathbf{r}_i$;t_i), estimation algorithm

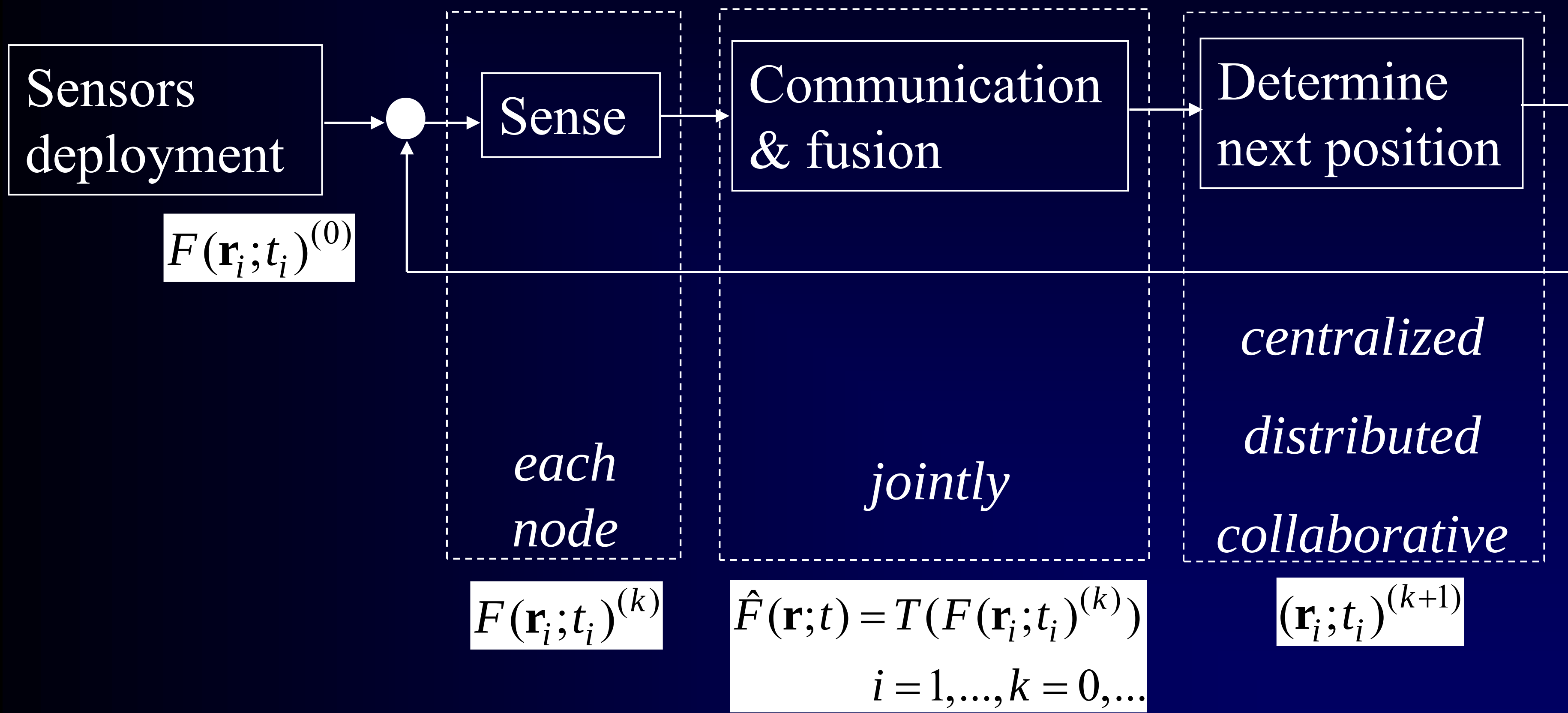
$$\hat{F}(\mathbf{r};t) = T\left(F(\mathbf{r}_i;t_i), \bar{F}(\mathbf{r};t)\right); \quad i = 1,\ldots,m)$$

  - *choose the* m *samples so to minimize the* a posteriori *uncertainty of the estimated field*

$$J = \iint E\{[F(\mathbf{r};t) - \hat{F}(\mathbf{r};t)][F(\mathbf{r};t) - \hat{F}(\mathbf{r};t)]\}d\mathbf{r}dt$$

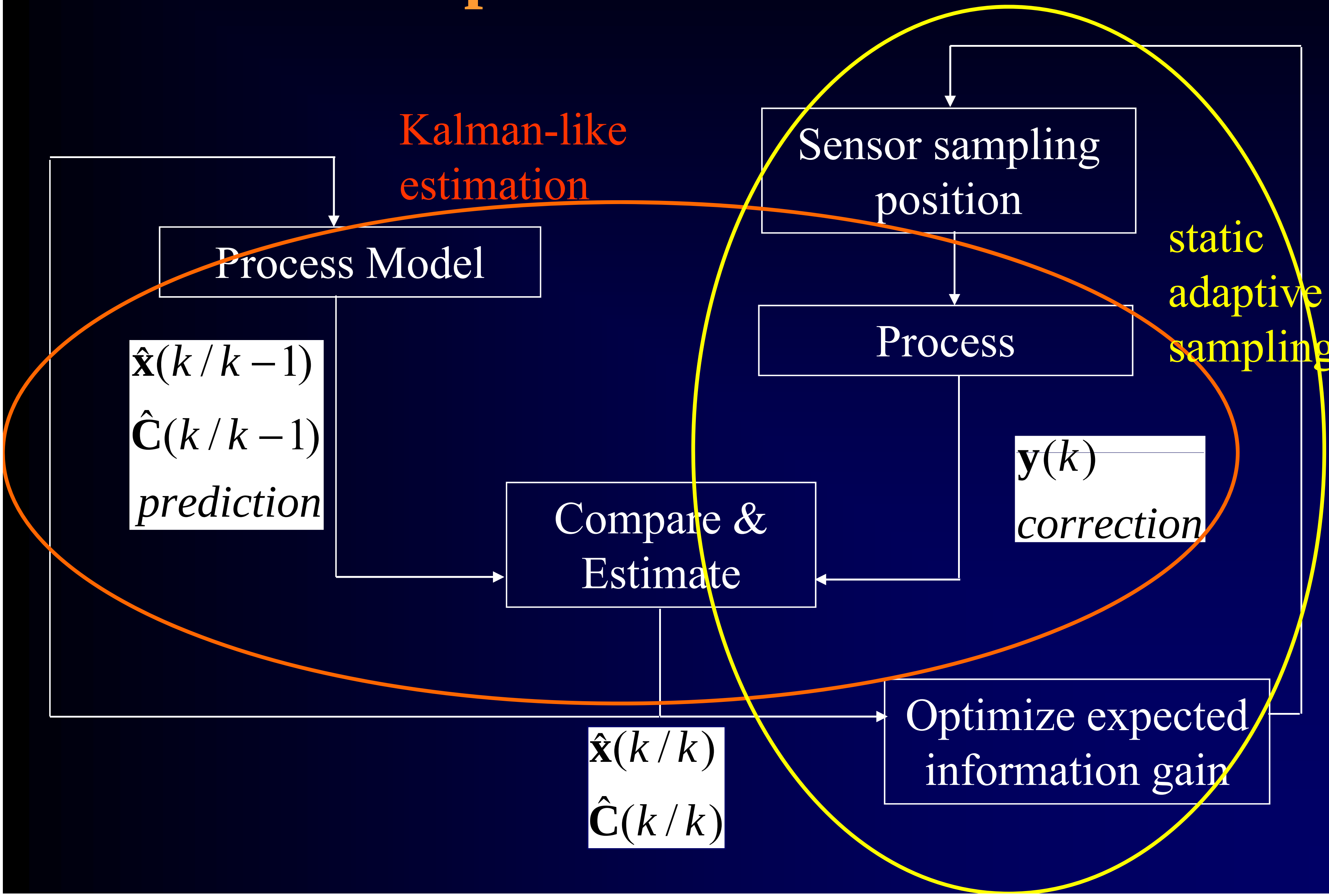
(adapted from Leonard et al., 07)

Adaptive sampling as a feedback process



(adapted from Huguenin & Rendas, 06)

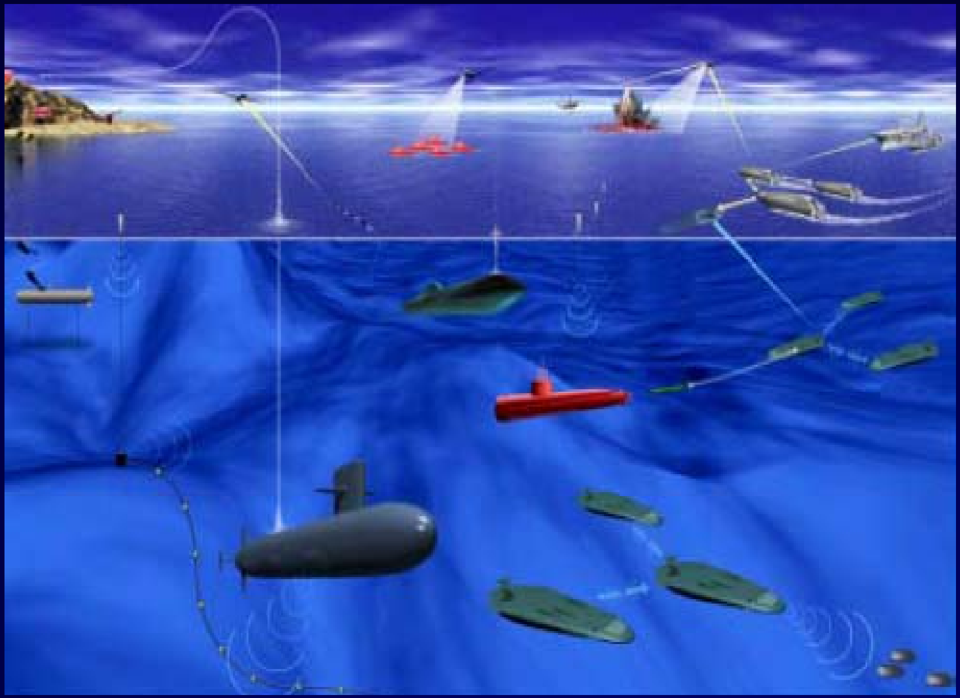
Model-driven predictor/corrector methods



Cooperation and coordination
(adapted from Whitcomb and Yuh, 09)

- Team of heterogeneous vehicles

- Payoff
  – adaptation
  – same/better performance
  – no single point weakness
  – optimized coverage
  – *sensor networks*
  – *ubiquitous computing*
  – *mobile agents, consensus, …*



- Drawback: ***cooperation and coordination require inter-vehicle communications***

The acoustic communication channel

- Transmission loss
  - affects SNR
  - limitations on channel capacity / requirements on source level
- Multi-path structure
  - causes symbolic interference
  - limitations on coding/decoding schemes
- Acoustic channel predictions used to determine relative ***depth***s and maximum ***range*** among Tx/Rx to guarantee a given SNR

Predicting channel characteristics from a communication stand-point

Acoustic Propagation equations:

$$SNR(x,w) = SL - TL(x,w) - N(w)$$

Equations for channel characterization

$$B_3 = \{w : w \in \mathcal{N}(w_0) : SNR(w) > SNR(w_0) - 3\}$$

[Bandwidth]

$$C_o = \int_{B_o} \log_2 \kappa \frac{|G(w)|^2}{n(w)} dw$$

[Capacity]

$$P_s = \int_{B} p_s^2(w) dw$$

[TX Power]

(Stojanovic, 07)

BellHop Numerical Code

- Simulates complex scenarios
  - environmental conditions
- Includes (in TL):
  - geometrical spreading
  - intrinsic attenuation
  - wave interference patterns
- Simplifications:
  - range independent
  - stationary sources

(Caiti et al., 09)

Limitations & opportunities for cooperative robots

• Network connectivity constraints limit the relative mobility of the agents

• *Mobility of the agents can be exploited to dynamically maximize some figure of merit of the communication channel*

What happens with COTS acoustic modems

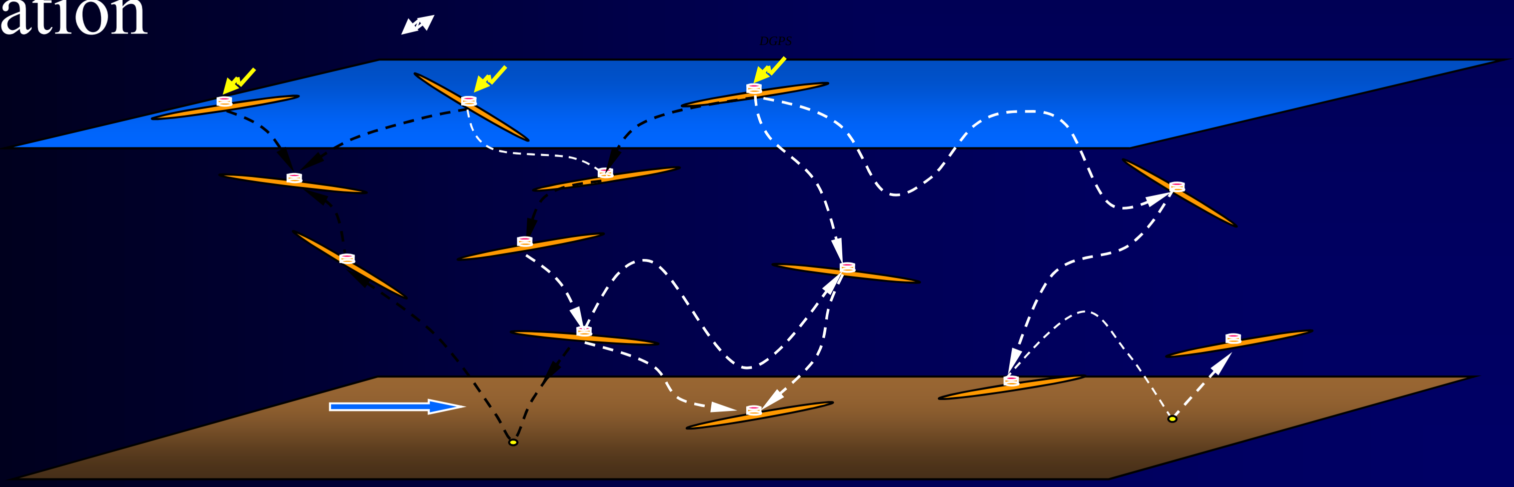
- COTS acoustic modems have fixed bit rate and source level, with BER depending on the SNR

- Bit rate: from 256 b/s to optimistic 15 kb/s

- ***Underwater cooperation has to rely on the autonomy of the individual agents and on parsimonious comms overhead***

Team localization

- A team of AUVs must be cheap!
- Underwater navigation is a major source of vehicle cost
  - inertial systems
- Use the acoustic modems also to localize acoustically the vehicles among the team with range-only measurements
- Some vehicles at the surface, geo-referenced; relative localization

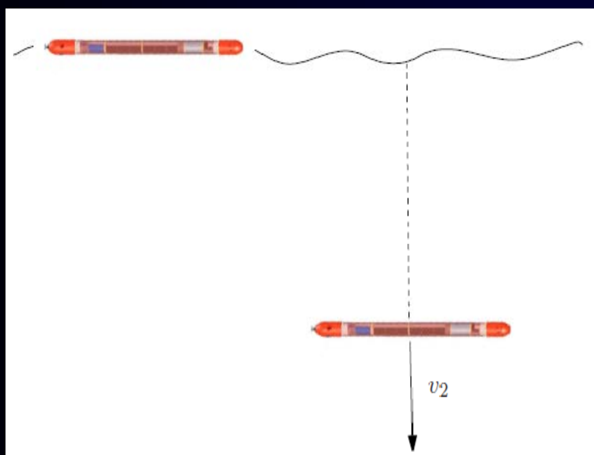


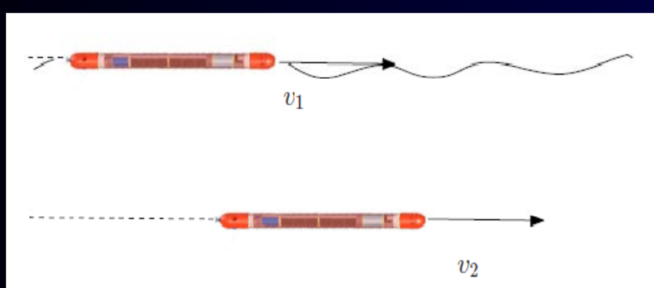
Cooperative uw localization by range-only measurements

- A hot research topics
  - J. Leonard; Sukhatme; Chitre; Antonelli ...
- Alternate between ranging and communication
- COTS modems available (WHOI, Evologics, ...)
- Use depth sensors to convert from 3D to 2D
- Several issues:
  - linear vs. nonlinear estimate
  - observability depending on relative vehicle motion
  - compensate for transmission delays
  - on-board correction for bended ray-paths
  - clock synchronization
- Our approach: *distributed EKF with delay* (from team theory work dating back to the '80s!)

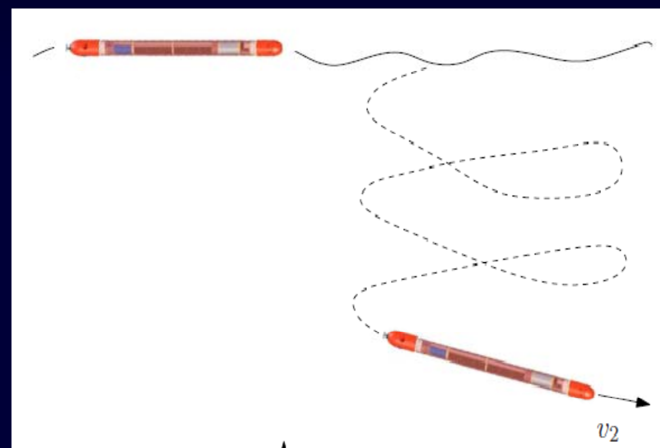
Designing behaviours to improve observability

Not observable

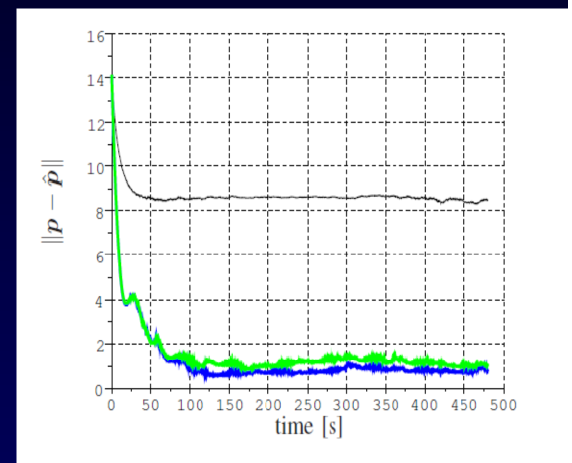


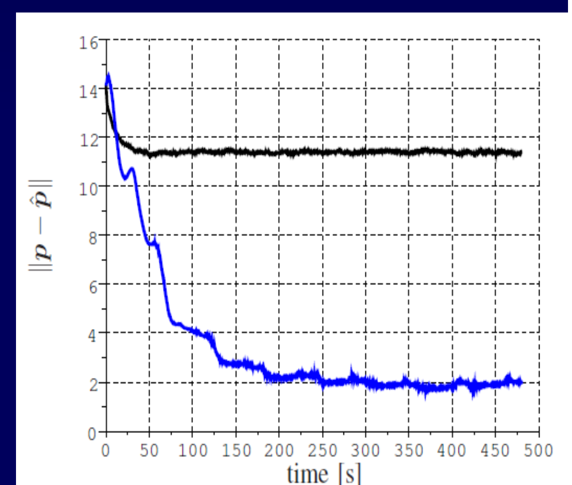


Observable



EKF Error

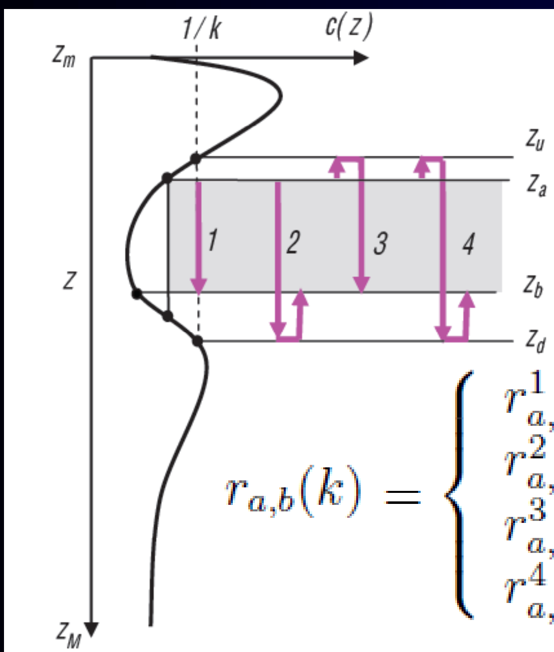




(Antonelli, Caiti et al., ICRA 10)

Real-time Ray-tracing (RT2)

- Compensate ray bending through a look-up table
- Bending ray error: increasing importance with range
- In distributed localization range errors will accumulate
- Requires measurement of sound-speed vs. depth



$$\tau_{a,b}(k) = \begin{cases} \tau^1_{a,b} = \Delta_{a,b} \\ \tau^2_{a,b} = \Delta_{a,b} + 2\Delta_{b,d} \\ \tau^3_{a,b} = \Delta_{a,b} + 2\Delta_{a,u} \\ \tau^4_{a,b} = \Delta_{a,b} + 2\Delta_{a,u} + 2\Delta_{b,d} \end{cases}$$

PTT:
Partial
Travelled
Times

$$r_{a,b}(k) = \begin{cases} r^1_{a,b} = \rho_{a,b} \\ r^2_{a,b} = \rho_{a,b} + 2\rho_{b,d} \\ r^3_{a,b} = \rho_{a,b} + 2\rho_{a,u} \\ r^4_{a,b} = \rho_{a,b} + 2\rho_{a,u} + 2\rho_{b,d} \end{cases}$$

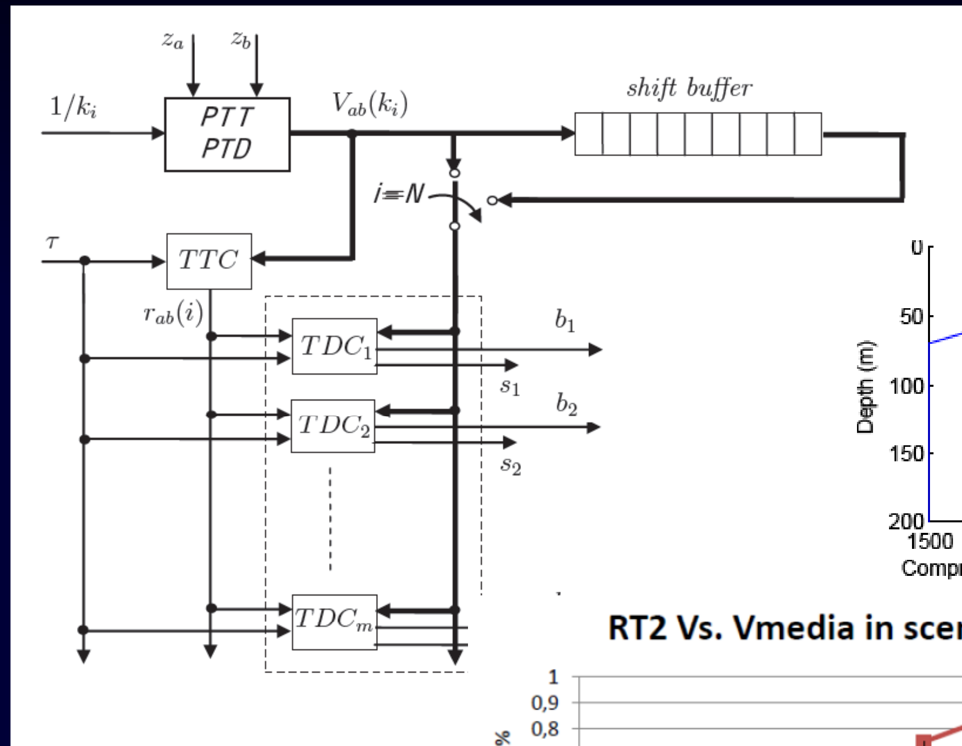
PTD:
Partial Travelled
Distances

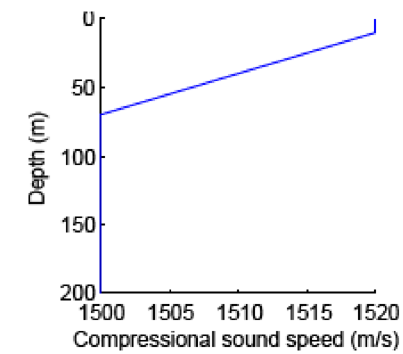
Look-up table and on-line estimate

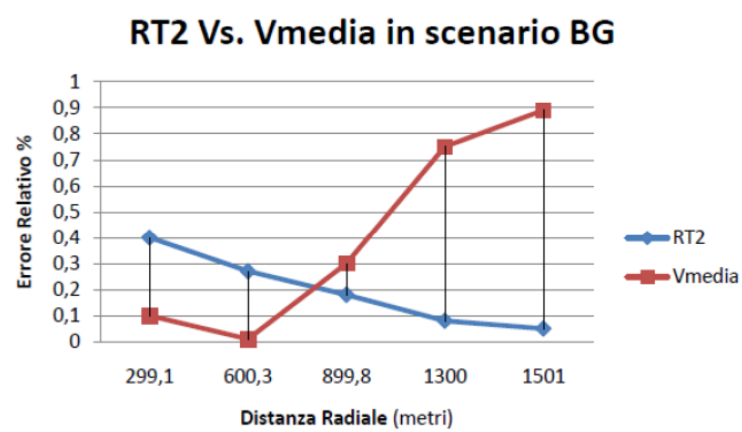
receiver depth

emitter depth

$$\begin{matrix} V_{11} & V_{12} & \cdots & V_{1n} \\ V_{21} & V_{22} & \cdots & V_{2n} \\ \cdots & \cdots & \ddots & \vdots \\ V_{n1} & V_{n2} & \cdots & V_{nn} \end{matrix}$$







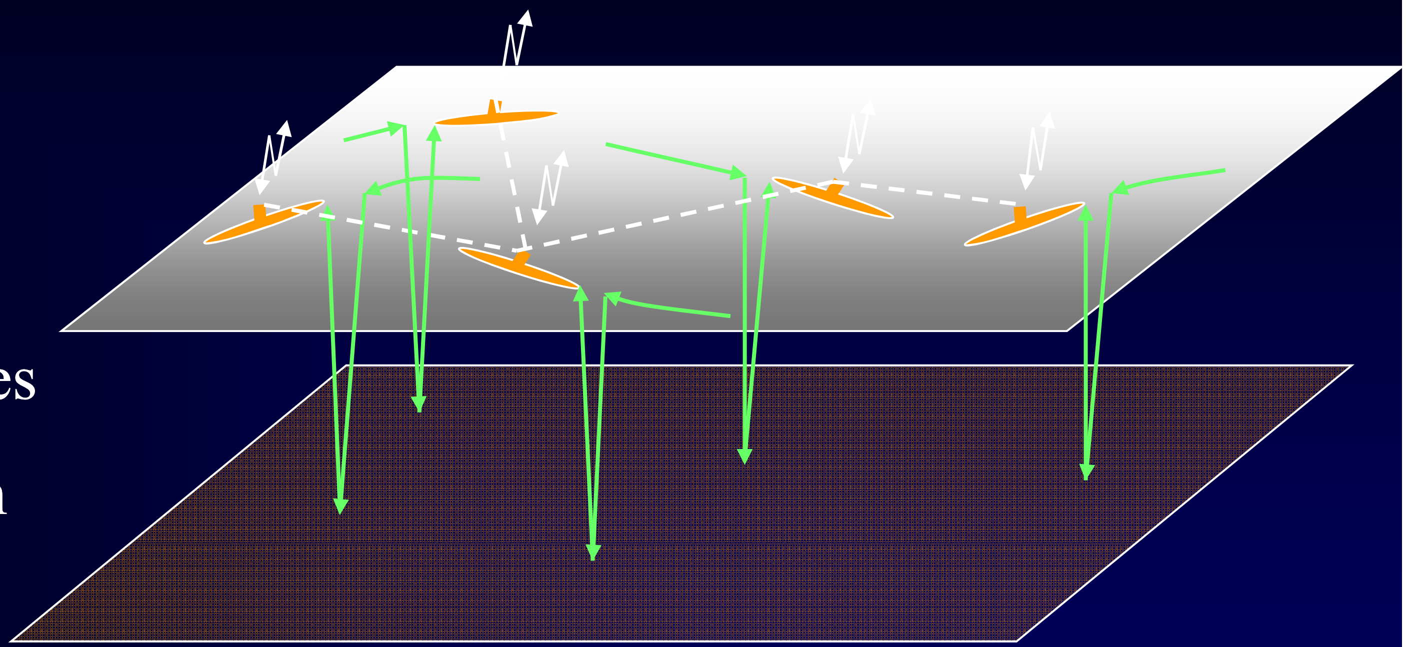
$$V_{ab} = [\, V_{ab}(k_1), V_{ab}(k_2), \cdots, V_{ab}(k_m) \,]$$

$$V_{ab}(k) = [T, \tau_{ab}^1, \tau_{ab}^2, \tau_{ab}^3, \tau_{ab}^4 \mid R, r_{ab}^1, r_{ab}^2, r_{ab}^3, r_{ab}^4] \Big|_k$$

(Casalino et al., Oceans' 10)

Cooperative adaptive sampling with communication constraints

- Each vehicle performs its own vertical sampling
- All the vehicles share information (acoustic)



plan the next move of the team in order to optimize:

- sampling map quality (map res. below a given threshold)
- overall area coverage measurements (cover the area by sampling where needed)
- *while maintaining connectivity*

⇒ **range constraint among the vehicles, varying in space and time**

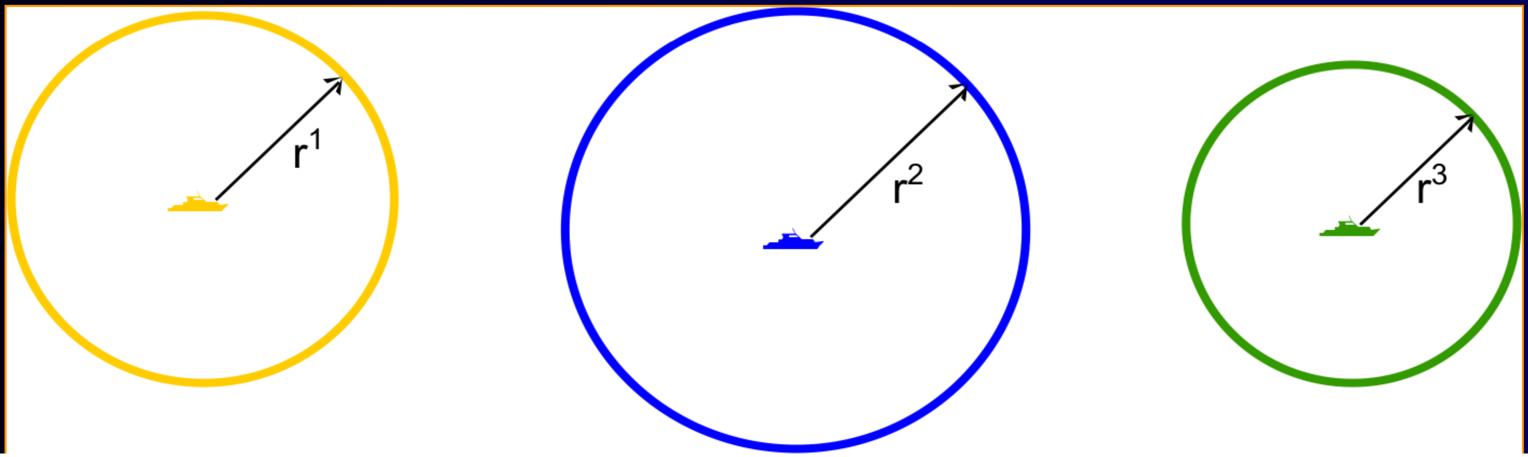
Sampling map quality: deterministic data-driven approach

Each vehicle computes its next admissible range for its next measurement (*admissible exploring radius*) on the basis of the local smoothness of the environmental map - *Local computations*

$$\hat{F}_I^{(k)}(\mathbf{r};t) = \sum_i^{\infty} h_i \phi_i(\mathbf{r};t)$$

$$\left\| F(\mathbf{r};t) - F_I^{(k)}(\mathbf{r};t) \right\| \cong \left\| F_I^{(k)}(\mathbf{r};t) \right\|_{\Phi} G_{\Phi}(h)$$

$\boldsymbol{\phi}$: RBF family
$\boldsymbol{h}$: fill distance
$\boldsymbol{G}$: known function

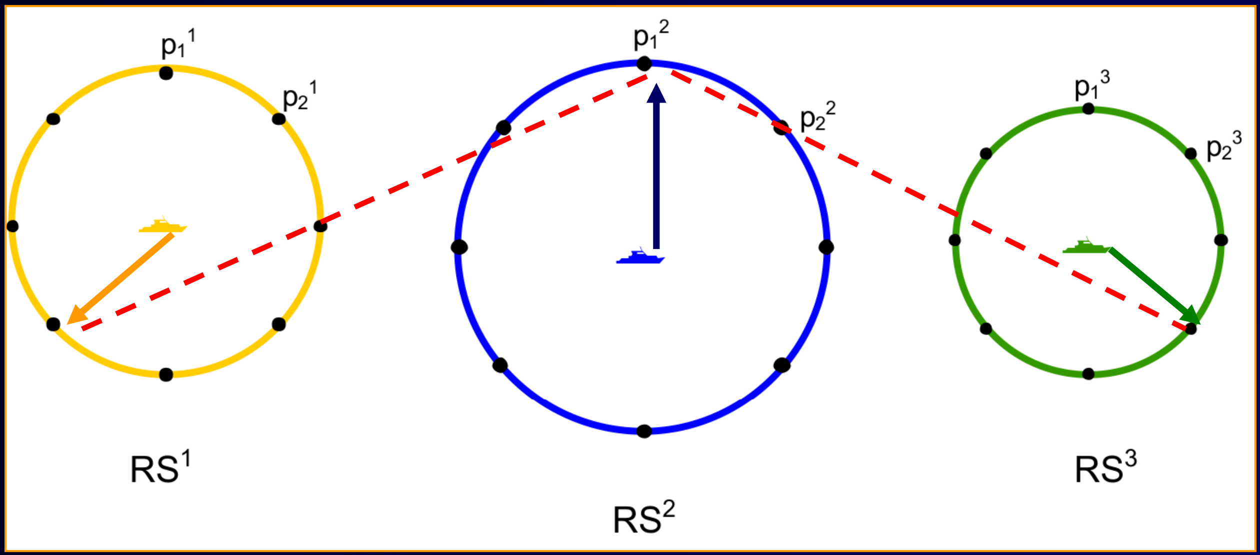


Optimize area coverage

Local decision, rule based: *maximize distance from previous samples and from next location of the other vehicles*

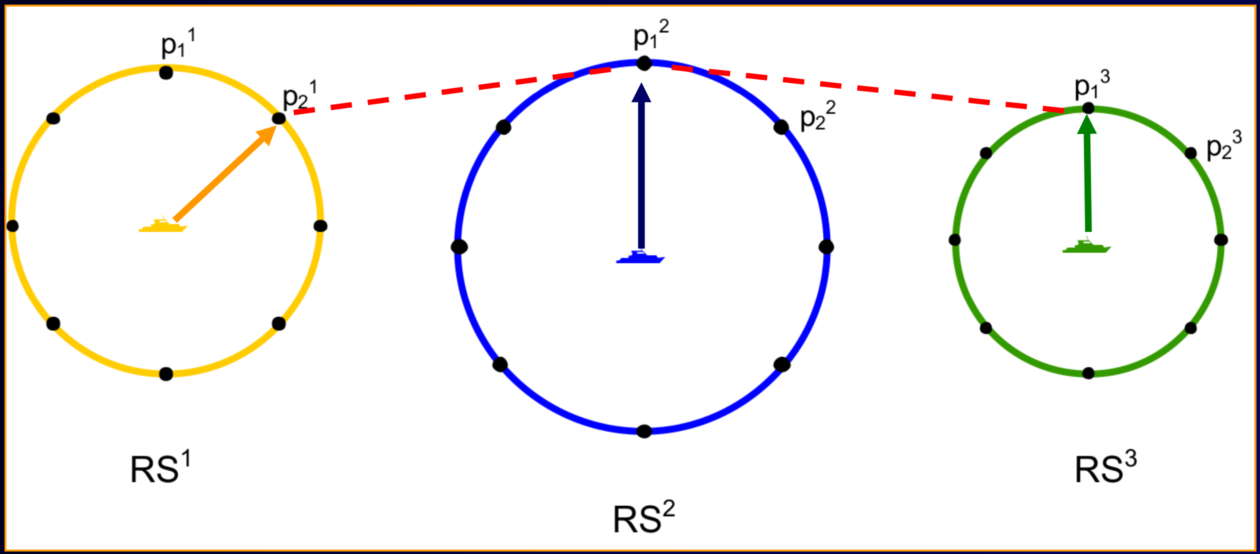
All vehicles apply the same rule to their available information set

Information exchange needed

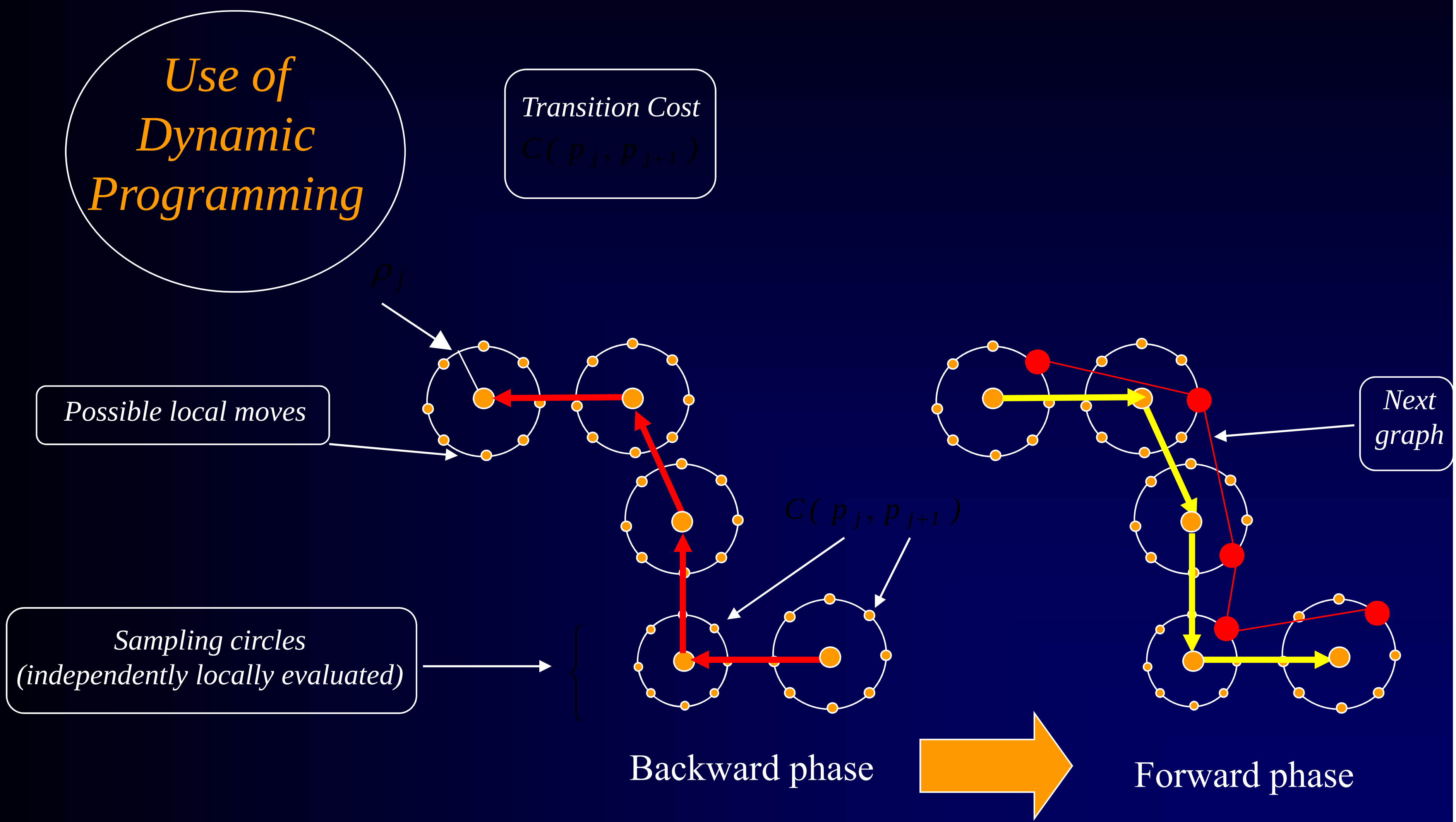


Communication/range constraint

Next sampling points must preserve connectivity of the communication structure



Serial graph structure, fixed topology

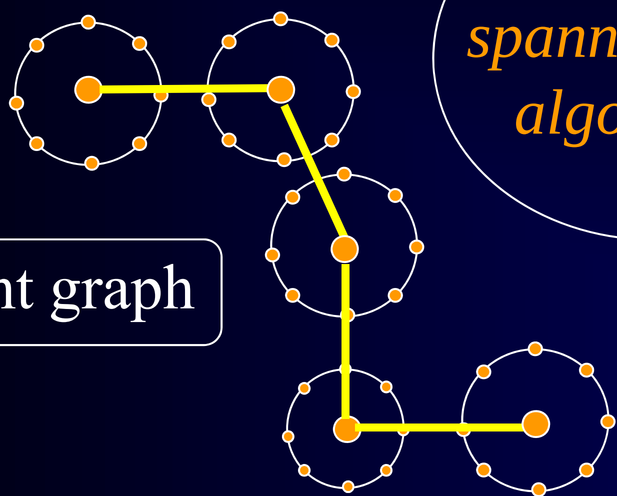


Distributed implementation of dynamic programming!

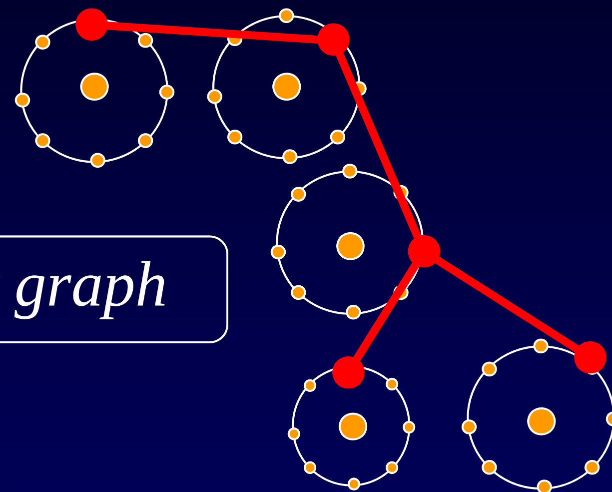
Articulated chain structure, adaptive topology

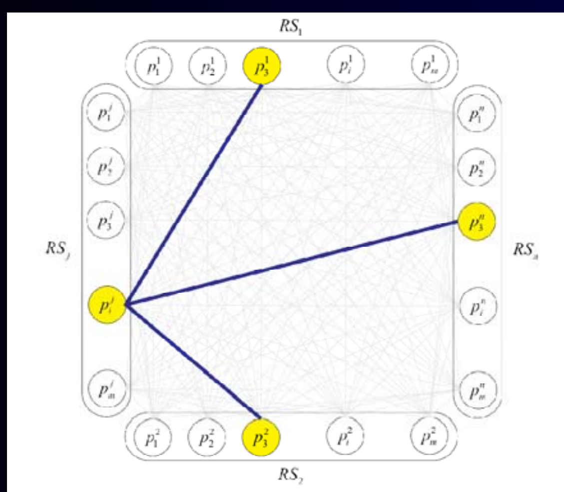
Minimum spanning tree algorithm

current graph

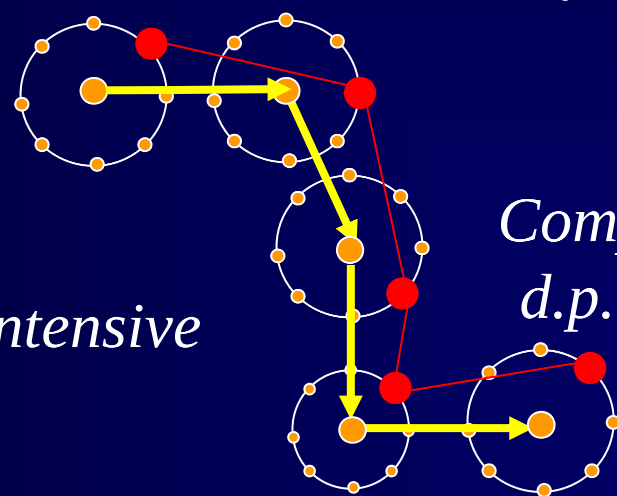


next graph



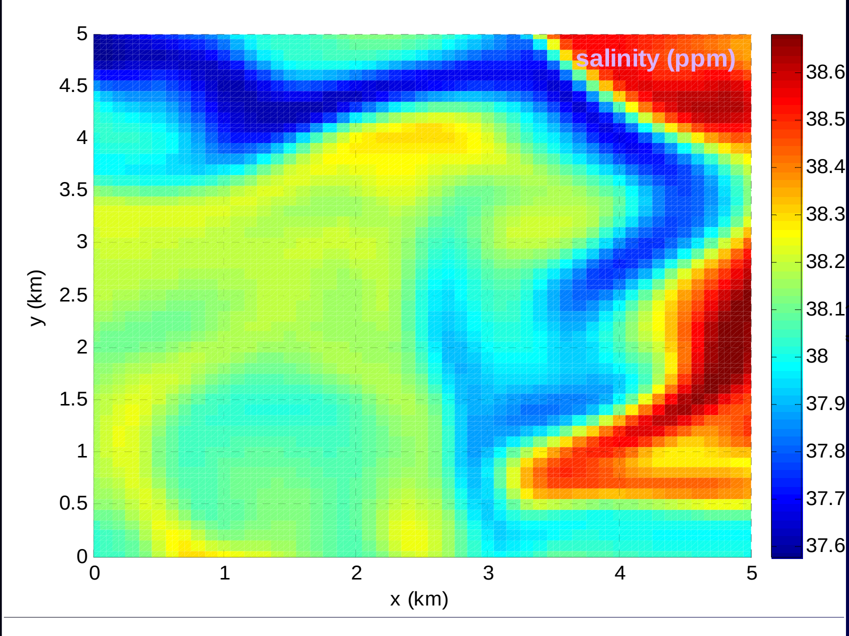


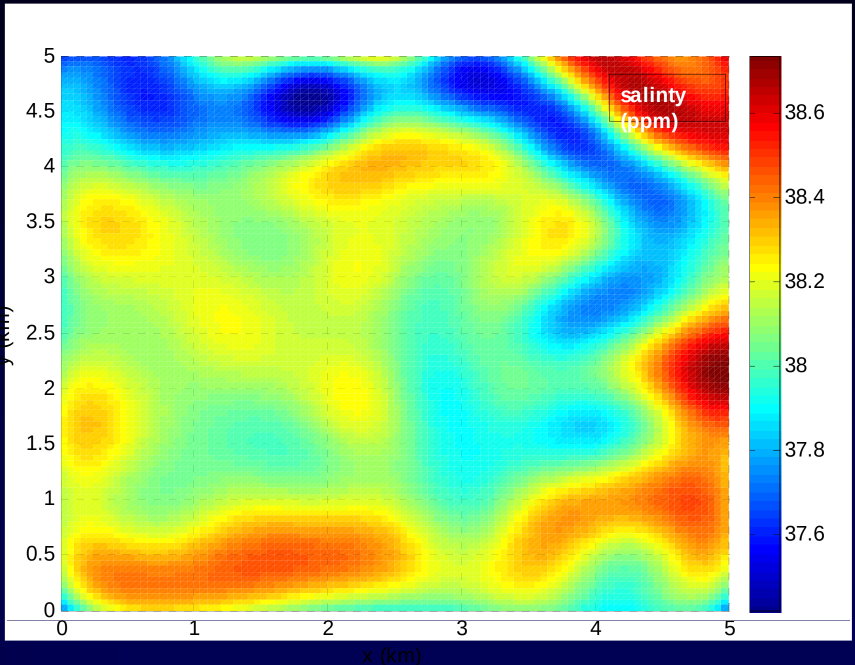
Comms intensive



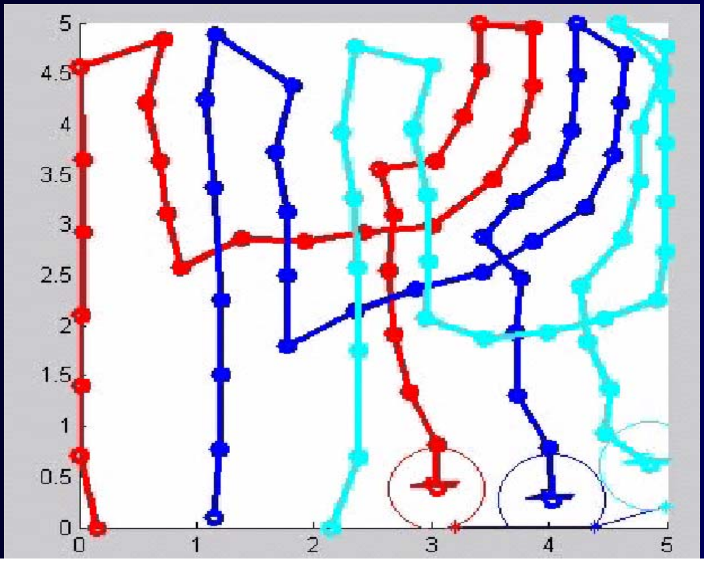
Compare with d.p. solution

Dynamic programming on test data





Test data, courtesy A. Alvarez, NURC



Reconstructed Via Cooperative Sampling and RBF interpolation

Graph theory based cooperation

- Sound optimality proof
- Distributed implementation of centralized algorithms
- Heavy comms overload
- Curse of dimensionality as the number of vehicles increase

- *Possibility of a truly local rule-based algorithm?*
- Yes – behaviours
- Different approaches and implementations – *no systematic design rule in general*, some cases analyzed
- Small comms load
- *Not always optimality guaranteed*

An example of cooperative algorithm in security application

- Goals
  - – Critical asset protection
  - – Maintaining acoustic connectivity among the team

- Each agent/node
  - –Builds a local map of channel characteristics and comms performance
  - –Updates the map when new environmental measurements become available
  - –Adapts its behaviour to tackle changes in the environment

- Rule-based behaviour and potential fields

(Caiti et al., 2009/10)

Rules of the game

- AUVs equipped with:
  - Acoustic modem– max range: R_C
  - Detection sonar – max range: R_D
  - Sensor to measure the environment (CTD)

$$\begin{cases} \min_{x_i} \sum_i \left\| x_a - x_i \right\|_2 \\ \left\| x_i - x_j \right\|_2 \geq R_D^i + R_D^j \ , \forall i, j \\ \forall i, \exists j : \left\| x_i - x_j \right\|_2 \leq R_C^i \end{cases}$$

cover with the sonars the greatest area around the asset to protect

- Find a solution with distributed decisions using only closest neighborhood information

Rule-based behaviour

- Rule 1: *Move toward the asset*

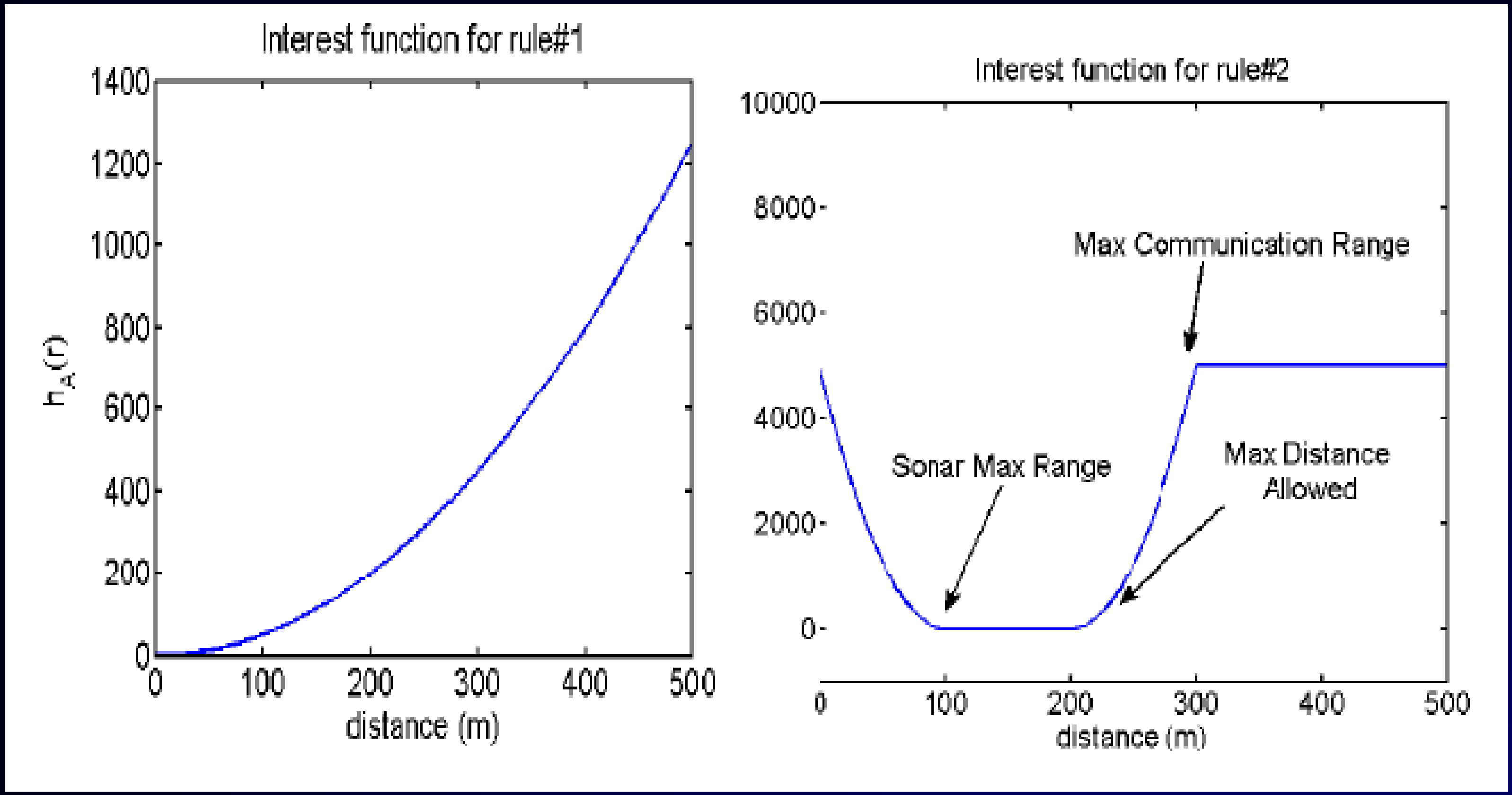
- Rule 2: *Move away from your closest neighbor*

- Implemented through gradients of artificial potential functions (*interest functions* - h_A, h_C)

- Vehicle course: vector sum of the two contributions

$$u(t) = u_A(t) + u_C(t) = \nabla h_A + \nabla h_C$$

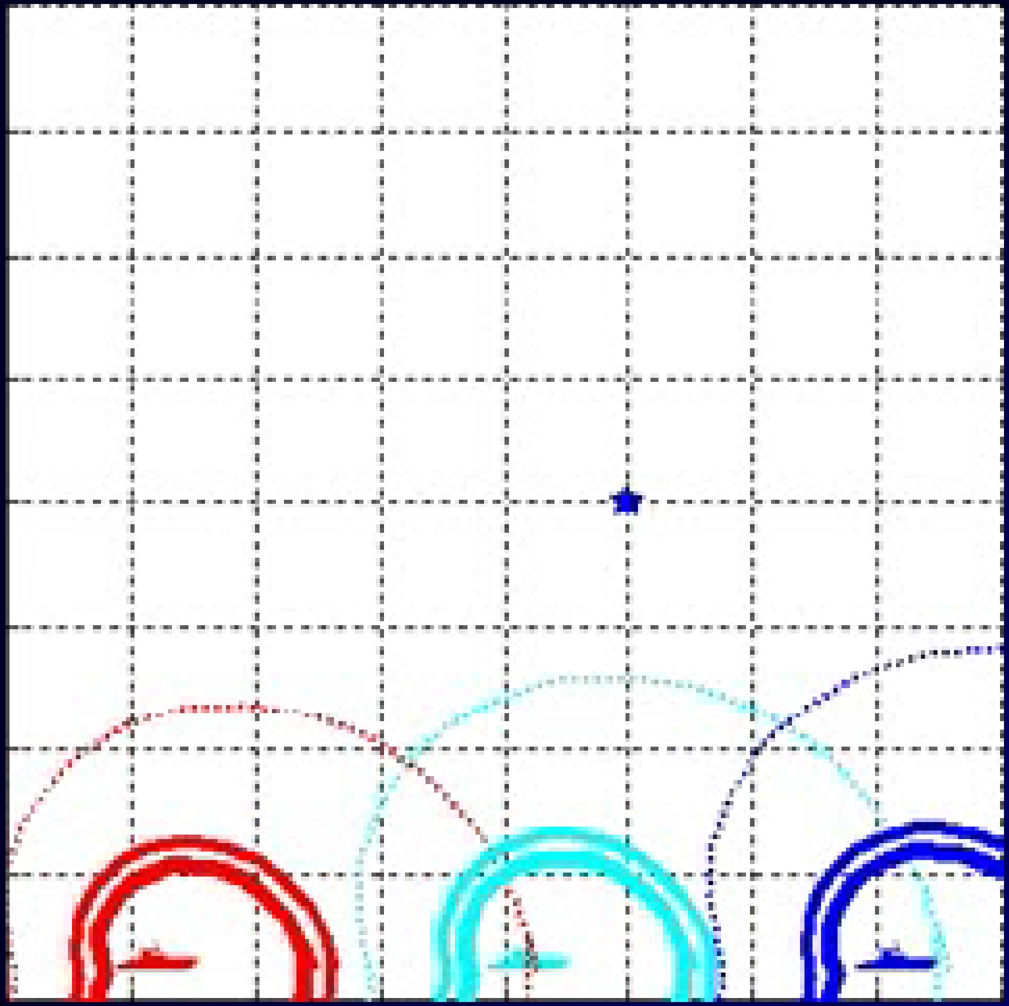
Interest functions



Ineherently robust to communication loss & equipment failure!

Can include sonar/modem directionality

Simulation results: 3 vehicles



Some formal properties

• With omnidirectional sonar/modems, infinite solution exists (all symmetric configurations around the asset)

• The rule-based algorithm stabilizes around one solution

• Analitycally, once on a solution the vehicles either stay where they are, or move keeping the symmetry around the asset (and spanning the whole set of solutions)

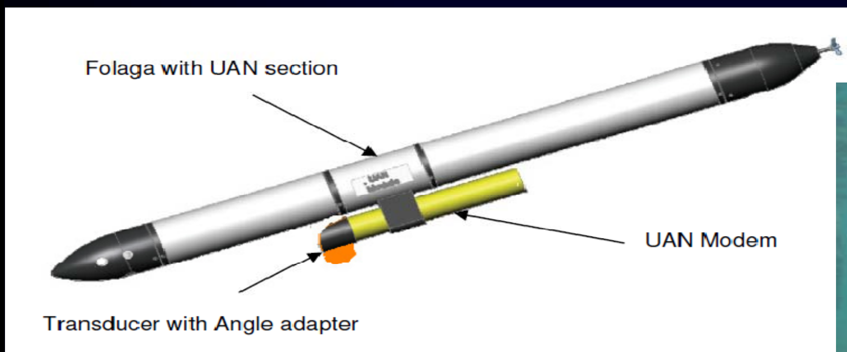
• We have never seen the symmetric motion in simulations; in practice it can be ruled out (note: the symmetric motion may be a plus, not a minus!)

Some more comments

- Small comms overhead
  - Each vehicle communicates with its closest neighbor
  - Data to be TX:
    - Agent Position
    - Maximum Detection Sonar Range
- Built in Emergency Procedure
  - If an agent loses comms goes to the asset
- Distributed, scalable algorithm, independent from AUV #
- Comms delay do not alter result, but imply longer vehicle paths and slower convergence

Experimental test

6-30 September 10, Pianosa Island



Networked communication
Cooperative localization
Security behaviour
2 vehicles

Conclusions

- **A set of tools for autonomous cooperative adaptive sampling with a team of AUV**
  - context: data-driven adaptation
  - deterministic and probabilistic metrics
  - acoustic communication prediction
  - cooperative distributed localization
- **Adaptation with communication constraints**
  - graph-theoretic approach
    - guaranteed optimality
    - less flexible, communication intensive
  - behaviour-based
    - robust
    - light comms
    - optimality and convergence not guaranteed but for special cases