Cooperative distributed localization and environmental sampling by AUV teams

Andrea Caiti (1,2), Pino Casalino (1,3), Andrea Munafò (1,2), Enrico Simetti (1,3), Alessio Turetta (1,3)

(2) DSEA & Centro Piaggio - University of Pisa, Italy  
(3) DIST – University of Genova, Italy

caiti@dsea.unipi.it
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
  - seafloor mapping
  - pre-programmed mission
- shallow water
  - some endurance
  - moderately expensive
  - oceanography, seafloor 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 mission
    - no autonomous planning needed (but autonomous navigation required)
    - open loop - feedback
  - Data driven:
    - use data to determine next way-point
    - 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

\[
F(r; t)\bigg|_{S_n} = \sum_{i=1}^{n} b_{i,r} F_i + c_{i,t} F_{i,t}
\]

\[
\left| F(r; t) \right|_{S_n} \leq k
\]

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

\[
F(r; t) = \sum_{i=1}^{\infty} h_i \phi_i(r; t) \quad h_i = \langle F; \phi_i \rangle
\]

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

- 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
    \[
    \bar{F}(\mathbf{r};t) = E\{F(\mathbf{r};t;\xi)\}
    \]
    \[
    C(\mathbf{r}, \mathbf{r}';t,t') = E\{[F(\mathbf{r};t) - F(\mathbf{r};t)][F(\mathbf{r}';t') - F(\mathbf{r}';t')]\}
    \]
  – *m* measurements at points \((\mathbf{r}_i, t_i)\), estimation algorithm
    \[
    \hat{F}(\mathbf{r};t) = T(F(\mathbf{r}_i; t_i), \bar{F}(\mathbf{r};t)); \quad i = 1, ..., m
    \]
  – 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

Sensors deployment → Sense → Communication & fusion → Determine next position

Each node

$F(r_i; t_i)^{(0)}$

$F(r_i; t_i)^{(k)}$

$F(r; t) = T(F(r_i; t_i)^{(k)})$

$i = 1, \ldots, k = 0, \ldots$

Centralized distributed collaborative

(Adapted from Huguenin & Rendas, 06)
Model-driven predictor/corrector methods

Kalman-like estimation

Process Model

\( \hat{x}(k / k - 1) \)
\( \hat{C}(k / k - 1) \)

prediction

Sensor sampling position

Process

\( y(k) \)
correction

Compare & Estimate

\( \hat{x}(k / k) \)
\( \hat{C}(k / k) \)

Optimize expected information gain

static adaptive sampling
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 **depths** 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**

- \( B_3 = \{ w : w \in N(w_0) : SNR(w) > SNR(w_0) - 3 \} \)  
  \[ C_o = \int_{B_0} \log_2 \kappa \frac{|G(w)|^2}{n(w)} dw \]  
  \[ P_s = \int_{B} p_s^2(w) dw \]

- (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

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

\[ r_{a,b}(k) = \begin{cases} 
\tau_{a,b}^1 = \rho_{a,b} \\
\tau_{a,b}^2 = \rho_{a,b} + 2\rho_{b,d} \\
\tau_{a,b}^3 = \rho_{a,b} + 2\rho_{a,u} \\
\tau_{a,b}^4 = \rho_{a,b} + 2\rho_{a,u} + 2\rho_{b,d} 
\end{cases} \]

**PTT**: Partial Travelled Times

**PTD**: Partial Travelled Distances
Look-up table and on-line estimate

\[ V_{ab} = \begin{bmatrix} V_{ab}(k_1) & V_{ab}(k_2) & \cdots & V_{ab}(k_m) \end{bmatrix} \]

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

(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

\[
\hat{F}_I^{(k)}(r; t) = \sum_{i}^{\infty} h_i \phi_i(r; t)
\]

\[
\|F(r; t) - F_I^{(k)}(r; t)\| \approx \left\| F_I^{(k)}(r; t) \right\|_{\Phi} G_{\Phi}(h)
\]

ϕ: RBF family
h: fill distance
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

Use of Dynamic Programming

Transition Cost $C(p_j, p_{j+1})$

Possible local moves

Sampling circles (independently locally evaluated)

Backward phase

Forward phase

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)

\[
\begin{align*}
\min_{x_i} & \sum_i \|x_a - x_i\|_2 \\
\|x_i - x_j\|_2 & \geq R_D^i + R_D^j, \forall i, j \\
\forall i, \exists j : \|x_i - x_j\|_2 & \leq R_C^i
\end{align*}
\]

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

Inherently 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

• Analytically, 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