Cooperative Path Planning for Multiple Autonomous Robotic Vehicles

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Outline

Why autonomous robotic vehicles?

- Reducing mission costs
- Reducing danger to humans

And why multiple autonomous robotic vehicles?

- Reducing mission costs – again
- Improving flexibility
- Achieving advanced goals more easily

Mission planning

- Find the best way of how to achieve a certain goal
- Cope with communication issues from base to vehicles as well as among the vehicles
- Deal with the propability of unexpected events $\rightarrow$ requires dynamic mission re-planning

Mission execution ❶ Dynamic environments

Vehicles operating in dynamic and uncertain environments always experience influences from these environments.

Direct influences

e.g. ocean drifts on AUVs, winds on UAVs

Indirect influences

e.g. appearing/disappearing dangers like anti-aircraft missile systems

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Mission execution ❷ Configuration changes

Vehicle swarms can also be affected by possibly occuring changes in the group configuration.

Immediate influences

e.g. at loss of vehicles the mission has to be replanned instantaneously or even cancelled in case a “specialist” got lost

“Long-term” influences

e.g. if the mission base sends additional vehicles for reinforcement of the swarm/replacing lost vehicles

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Designing an AUV-based spectral classifier
[Y. Zhang et al.]

- Relating observations from a moving platform to the temporal-spatial spectrum of the process under survey (mingled-spectrum principle)
- Utilizing temporal-spatial information, AUVs can distinguish between oceanographic processes

⇒ AUVs can directly be used as classifier of these processes (instead of reconstructing these processes from the collected data)

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Performance metrics ❶ Improving vehicle design
[J. S. Willcox et al. (1)]

- Most mission critical point is energy consumption of the individual vehicles
- Energy is minimized by reducing the travelling distance and optimizing the speed of each individual vehicle
- This has an influence on survey time and survey resolution

⇒ Possibility to measure the influence of a vehicle's design on the overall survey performance

⇒ Allows for adapting parameters like *hotel load*, *propulsion efficiency* and *maximum velocity*

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Performance metrics ❷ Estimating a mission's quality

[J. S. Willcox et al. (1), N. E. Leonard et al. (1), J. G. Bellingham et al., J. S. Willcox et al. (2), N. E. Leonard et al. (2)]

Synoptic performance metric

- Mapping an ocean structure must be faster than significant changes occur in that structure
- Trade-off between errors introduced through temporal smearing (ocean's evolution during survey) and errors through undersampling (decreasing survey distance because of energy concerns)

⇒ Defining an error measure on these points allows for survey parameter optimization like *covered area*, *survey time* and *number of vehicles*

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The "optimal dataset"

- Designing mobile sensor networks towards optimal data collection
- Metric provides a measure of model uncertainty as a function of where and when data is collected – reduced uncertainty implies better coverage

⇒ Allows statements on how a particular collected dataset reduces the error in the model

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Mathematical Background I
[J. S. Willcox et al. (1), J. G. Bellingham et al.]

Energy Analysis

AUV energy consumption is determined by three parameters: survey area, survey resolution and total completion time.

Let λ be the spatial resolution of a simple grid survey over a fixed square area A. (For a rectangular area with both sides significantly larger than λ, the following approximation is good.) The total linear distance traversed in the survey is then

$$L \approx \frac{A}{\lambda} - \lambda \approx \frac{A}{\lambda}$$

Mathematical Background II
[J. S. Willcox et al. (1), J. G. Bellingham et al.]

The vehicle speed to complete a survey in a given time is given by

$$V = \frac{L}{\tau} \approx \frac{A}{\lambda\tau}$$

Given V and τ, the total energy consumption for a survey is

$$E_{\text{tot}} = \left[\frac{\rho C_d S V^3}{2\eta} + H\right]\tau$$

Mathematical Background III
[J. S. Willcox et al. (1), J. G. Bellingham et al.]

Physical AUV Parameters

- ρ density of water
- C_d drag coefficient for the vehicle
- S the vehicle's wetted surface area
- η propulsion efficiency
- H vehicle hotel load (power consumed by electronics, sensor systems, etc.)

Mathematical Background IV
[J. S. Willcox et al. (1), J. G. Bellingham et al.]

E_{tot} decreases with decreasing V and/or τ. Since these cannot increase simultaneously without changing the survey resolution, they must be tradeoff to minimize E_{tot}. If the total consumed energy is divided by the total survey distance, the equation for the energy consumption per unit distance is

$$\frac{E_{\mathrm{tot}}}{L} = \frac{\rho C_d S V^2}{2\eta} + \frac{H}{V}$$

Mathematical Background V
[J. S. Willcox et al. (1), J. G. Bellingham et al.]

To get the optimal vehicle speed, we take the derivative of this with respect to velocity and set this to zero.

$$V_{\text{opt}} = \left(\frac{H\eta}{\rho C_d S} \right)^{1/3}$$

V_{opt} is optimal in the sense that it minimizes energy consumption per unit distance travelled. By substitution, the minimum total energy consumption can be found:

$$E_{\text{min}} = \frac{3LH}{2V_{\text{opt}}} = \frac{3}{2}\tau H$$

Adaptive Sampling
[E. Fiorelli et al.]

- Attempting to increase survey efficiency by concentrating measurements in regions of interest
- Reduces expected energy and time of a survey

⇒ Can be done at mission planing time (static), e.g. appropriately sized grid surveys as well as execution time (dynamic), e.g. coupling observations to mission modeling

⇒ Reactive approach to data collection

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Knowledge management
[N. M. Patrikalakis et al.]

- In ocean research, a multiplicity of disciplines comes together
- Sharing data and software among these disciplines is necessary
- Mission planning has therefore to be done on a common base

⇒ Definition of metadata providing easy access to a distributed computing and networking infrastructure for bringing together approaches of the various disciplines

⇒ Automatic mission workflow creation to relieve mission planners from having to consult other experts first

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Adaptive gradient climbing
[R. Bachmayer et al., P. Ögren et al.]

- A group of autonomous vehicles can be understood as mobile, reconfigurable and intelligent sensor array

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Virtual bodies for swarm control

[N. E. Leonard et al. (1), P. Ögren et al., N. E. Leonard et al. (2)]

- Strongly interconnected with swarm behaviour
- Network is considered as *one* virtual body formed by a collection of moving reference points called "virtual leaders"
- Dynamics are computed centrally and broadcast to vehicles in the group

⇒ Each vehicle uses exactly the same control law

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Artificial potentials

[E. Fiorelli et al., N. E. Leonard et al. (1), P. Ögren et al., N. E. Leonard et al. (2)]

- Defining behaviour among various vehicles inside a virtual body through using a virtual attracting force among the vehicles

⇒ Using the center of mass of a *virtual body*, optimal distances are computed

⇒ Allows decoupling of the formation stabilization problem from gradient climbing missions

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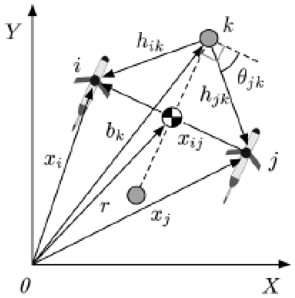
Mathematical Background I
[R. Bachmayer et al., E. Fiorelli et al.]

Virtual Bodies and Artificial Potentials (VBAP)

Designed for vehicles moving in $\mathbb{R}^3$; here we concentrate on the 2-dimensional case.



Mathematical Background II
[R. Bachmayer et al., E. Fiorelli et al.]

With respect to an inertial frame, let

- $x_i \in \mathbb{R}^2$, $i = 1, \ldots, N$ the vehicle position vectors
- $b_k \in \mathbb{R}^2$, $k = 1, \ldots, M$ the virtual leader position vectors

Then $r = (1/M) \sum_{k=1}^{M} b_k \in \mathbb{R}^2$ is the position vector to the center of mass of the virtual body. Let $x_{ij} = x_i - x_j \in \mathbb{R}^2$ and $h_{ik} = x_i - b_k \in \mathbb{R}^2$. Let $u_i \in \mathbb{R}^2$ be the control force on the ith vehicle. With full actuation, the dynamics for $i = 1, \ldots, N$ are

$$\ddot{x}_i = u_i$$

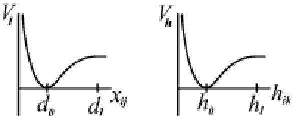
Mathematical Background III
[R. Bachmayer et al., E. Fiorelli et al.]

Let $V_I(x_{ij})$ and $V_h(h_{ik})$ be artificial potentials between a pair of vehicles i and j and a vehicle i and a virtual leader k, respectively. Let $V_r(\theta_{ik})$ an additional potential orienting the angles $\theta_{ik} = \arg h_{ik}$. The control law for the ith vehicle is defined as

$$u_i = -\sum_{j \neq i}^{N} \nabla_{x_i} V_I(x_{ij}) - \sum_{k=1}^{M} (\nabla_{x_i} V_h(h_{ik}) + \nabla_{x_i} V_r(\theta_{ik}))$$

Mathematical Background IV
[R. Bachmayer et al., E. Fiorelli et al.]

Using the typical form for V_I and V_h shown below, V_I yields a force acting attracting or repelling if $||x_{ij}|| \gtrless d_0$ and zero when the vehicles are very far apart ($||x_{ij}|| \geq d_1 > d_0$) or when $||x_{ij}|| = d_0$, where d_0 and d_1 are constant design parameters. $V_r(\theta_{ik})$ is designed so that it has isolated global minima at specified angles about the virtual leader.



Considering Dynamic and Uncertain Environments
[J. S. Bellingham et al.]

Changes in fleet

Ignoring the propability of vehicle loss results in mission plans that are likely to fail

Environmental changes

Addition/removal of obstacles also needs on-demand mission replanning

⇒ Central idea to each approach is waypoint reassignment according to stochastic properties (e.g. costs of adding a certain waypoint to a certain vehicle's trajectory)

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Acoustic networks
[H. Schmidt et al.]

- Combining a network of AUVs with acoustic tomography
- Allows to match the high coverage capability of acoustic tomography with the high resolution capability of mobile platforms

$\Rightarrow$ Reducing the trade-off between coverage and resolution

$\Rightarrow$ Also an additional approach to *adaptive sampling*

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Summary

- A system of coordinatedly acting multiple vehicles has a lot of advantages compared to one single vehicle
- New issues arise for mission planning, but on the individual vehicle level, things become easier
- Metrics considering “mission quality” are used to improve vehicle and mission parameters

Opinion

+ Proof of neccessity of multiple vehicles [J. G. Bellingham et al.]
+ Cooperation can achieve goals which a single vehicle would hardly be able to manage, and not with the same time and quality
+ Intelligent mission planning can to be done in advance (but the resulting plans have to be dynamically changeable)
+ Performance metrics provide a measure to determine mission plan and vehicle capabilities
- Communication among vehicles does not take place
- It is not said how coordinated gradient descent can be achieved outside simulations without communication/terms of measuring their own and the position of other vehicles

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