Ocean Modelling 94 (2015) 46–66

Contents lists available at ScienceDirect

Ocean Modelling

journal homepage: www.elsevier.com/locate/ocemod

Path planning in multi-scale ocean flows: Coordination and dynamic obstacles

T. Lolla*, P.J. Haley Jr., P.F.J. Lermusiaux*

Department of Mechanical Engineering, Massachusetts Institute of Technology, 77 Mass. Ave., Cambridge, MA 02139, United States

ARTICLE INFO

Article history:
Received 10 February 2015
Revised 22 June 2015
Accepted 23 July 2015
Available online 4 August 2015

Keywords:
Ocean forecasting
Coordination
Swarm formation control
Obstacle avoidance
Level-set
Time optimal path planning
Underwater vehicles
UAV

ABSTRACT

As the concurrent use of multiple autonomous vehicles in ocean missions grows, systematic control for their coordinated operation is becoming a necessity. Many ocean vehicles, especially those used in longer-range missions, possess limited operating speeds and are thus sensitive to ocean currents. Yet, the effect of currents on their trajectories is ignored by many coordination techniques. To address this issue, we first derive a rigorous level-set methodology for distance-based coordination of vehicles operating in minimum time within strong and dynamic ocean currents. The new methodology integrates ocean modeling, time-optimal level-sets and optimization schemes to predict the ocean currents, the short-term reachability sets, and the optimal headings for the desired coordination. Schemes are developed for dynamic formation control, where multiple vehicles achieve and maintain a given geometric pattern as they carry out their missions. To do so, a new score function that is suitable for regular polygon formations is obtained. Secondly, we obtain an efficient, non-intrusive technique for level-set-based time-optimal path planning in the presence of moving obstacles. The results are time-optimal path forecasts that rigorously avoid moving obstacles and sustain the desired coordination. They are exemplified and investigated for a variety of simulated ocean flows. A wind-driven double-gyre flow is used to study time-optimal dynamic formation control. Currents exiting an idealized strait or estuary are employed to explore dynamic obstacle avoidance. Finally, results are analyzed for the complex geometry and multi-scale ocean flows of the Philippine Archipelago.

1. Introduction and motivation

The simultaneous use of multiple agents enables complex tasks to be completed in a coordinated and robust manner. In nature, coordination is commonly exhibited by bees, birds, ants, and other animals when they perform activities such as foraging, navigation and hunting. Coordination also improves the overall performance of teams of autonomous robots. Multi-agent systems are then also versatile and effective in completing tasks such as exploring, mapping and monitoring. To execute such tasks, single agent approaches may either be much slower or much more sensitive to disruptions and uncertainties.

Coordination among Autonomous Underwater Vehicles (AUVs) such as gliders and propelled vehicles (including surface crafts such as kayaks) is now feasible in various types of ocean sampling and exploratory missions due to major advances in manufacturing (Yuh, 2000), vehicle reliability (Bahr et al., 2009; Fiorelli et al., 2004), robotics (Bellingham and Rajan, 2007) and autonomy (Curtin and Bellingham, 2009; Curtin et al., 1993; Hagen et al., 2007; Lermusiaux et al., 2015). Equipped with sensors to observe the pertinent ocean features, AUV teams can sample the ocean adaptively (Fiorelli et al., 2004; Leonard et al., 2010; Lermusiaux et al., 2007; Ramp et al., 2009; Smith et al., 2011; Wang et al., 2009), enabling individual units to exploit the information gathered by other group members (Bahr et al., 2009; Paley et al., 2008). To do so, trajectories of underwater vehicles need to be planned, which is challenging. As AUVs are susceptible to ocean currents, their trajectories can be greatly influenced by the flows they encounter (Lolla et al., 2014a; 2014b). Therefore, autonomous planning should account for predicted currents, especially when they are strong and dynamic. Additionally, AUVs often operate in sea environments with physical obstacles or with ‘forbidden’ regions, either of which can be dynamic. As a result, ideal autonomous coordination should integrate ocean modeling with sensing, planning, control, estimation and optimization.

As ocean flows are characterized by numerous spatial and temporal scales, multi-vehicle tasks also encompass a wide range of scales. In our applications, vehicles scales (meter and second) are assumed shorter and faster than the flow scales of interest. Nonetheless, for smaller-scale ocean missions, specific vehicle speeds and pattern formations can be critical. When a group must function as a

* Corresponding authors. Tel.: +1 617 324 5172; fax: +1 617 324 3541.
E-mail addresses: ltapovan@mit.edu (T. Lolla), phaley@mit.edu (P.J. Haley Jr.), pierrel@mit.edu (P.F.J. Lermusiaux).

http://dx.doi.org/10.1016/j.ocemod.2015.07.013

communication network, spatial scales are limited by transmission losses that increase with range. Small sampling scales are also needed to characterize sub-mesoscale or turbulent features such as microstructures, eddies and algae patches. In larger-scale missions, underwater vehicle-to-vehicle communication may be impractical. One may then be interested in optimizing the endurance of the swarm (Subramani et al., 2015) or in observing ocean processes such as mesoscale fronts, coastal upwelling and relaxation events, basin-scale current systems or coherent structures (Haley et al., 2009; Michini et al., 2014; Reed and Hover, 2014; 2013; Rudnick et al., 2004; Schmidt et al., 1996; Schofield et al., 2010). Similarly, for other sampling applications, either slow or fast temporal scales may drive the mission (Fiorelli et al., 2004; Leonard et al., 2007).

This paper presents a methodology for distance-based coordination of underwater vehicles operating in minimum-time within multi-scale ocean flows, combining ocean modeling with a level-set approach and optimization for coordinated motions. A critical question is: can a group of AUVs be controlled to form and maintain prescribed shapes or patterns while carrying out a mission, regardless of the ocean currents?; and if so, how? The goal of formation control, a specific type of distance-based coordination, is to have a group of vehicles organize into stable patterns, including geometrical shapes such as triangles, squares, or lines. Presently, we combine such coordination with time-optimal path planning. Applications include transportation, surveillance, exploration, inspection and distributed sensing (Jouvencel et al., 2010; Lolla, 2012; Mallory et al., 2013). While single-vehicle missions provide local data on currents, temperature and salinity, multi-vehicle missions coordinated through pattern formation enable the direct estimation of gradients and variability, which is fundamental.

A second contribution of this paper is a technique to compute time-optimal trajectories of AUVs operating in the presence of dynamic obstacles and forbidden regions. Obstacles such as islands or ships block the ocean currents as well as the vehicles. However, forbidden regions are open sea regions that the vehicles must avoid. Examples include fishing zones, polluted or dangerous areas, or regions to stay clear of in order to remain undetected. A simple example with stationary forbidden regions was provided in Lolla et al. (2012). Presently, we consider dynamic forbidden regions in realistic settings and develop the solution technique. Such dynamic time-optimal problems amount to a coordination among the AUVs and the variable obstacles.

Pattern formation control (Bendjilali et al., 2009; Swaminathan and Minai, 2005) has algorithms falling broadly into three categories. The first consists of *behavior-based* approaches, in which the desired behaviors (collision avoidance, formation keeping, target seeking etc.) are prescribed to each robot (Arkin and Balch, 1998) and the final robot control is derived by weighing the relative importance of each behavior. This method is flexible and can guide the robots through uncertain environments using only the local sensor information. *Virtual-structure* approaches constitute the second category of formation control algorithms, where the entire group is considered as a virtual rigid structure, so that the whole robotic system is analogous to a physical object (Ren et al., 2003). Trajectories are not assigned to individual robots, but to the entire unit as a whole. In *leader–follower* approaches for formation control, some of the agents are labeled as the *leaders* and their trajectories are pre-computed. The remaining vehicles (followers) form and maintain a desired posture around the leaders. Such methods have been widely studied, both for holonomic (Bendjilali et al., 2009; Desai, 2002; Dimarogonas et al., 2009) and non-holonomic (Consolini et al., 2007) robots operating in stationary environments, also considering noisy communications among vehicles (Ren and Sorensen, 2008; Sisto and Gu, 2006). Leader–follower methods are scalable and relatively easy to implement. However, planning follower trajectories that are robust to faults in the leaders' trajectories remains an active challenge. Graph search (Desai, 2002) and potential field methods (Jouvencel et al., 2010) are among the different techniques used to compute the trajectories of the follower vehicles.

Potential field methods for cooperative formation control define artificial force laws between pairs of robots or robot groups in order to attain a prescribed formation (Jouvencel et al., 2010; Reif and Wang, 1999; Yang and Zhang, 2010). Different types of potential-, fluid- and force-fields have been studied (Fierro et al., 2002; Leonard and Fiorelli, 2001; Pimenta et al., 2013; Sabattini et al., 2011; Zhang and Leonard, 2007). Other formation control methods use implicit shape functions (Chaimowicz et al., 2005). In such methods, the desired shape is set as the zero-contour of a suitable function and vehicles are then controlled by a gradient descent technique to achieve the desired shape. The algorithm may be augmented with artificial robot-to-robot repulsion to spread the robots uniformly along the contour. This approach provides flexibility in the formation shape and is suitable for a range of swarm sizes (Esin et al., 2008; Paley et al., 2008; Zhang et al., 2007). Convex optimization techniques for formation control in swarms are discussed in Derenick and Spletzer (2007), and extended to handle dynamic obstacles in Liu et al. (2011). For more reviews on pattern formation control, we refer to Lolla (2012).

In most of the above formation control studies, the kinematics of the vehicles is not affected by the environment. Yet, underwater vehicles have limited operating speeds, and dynamic ocean currents should be accounted for. For time-optimal path planning without coordination, we can utilize recent level-set equations that apply to regular ocean flows (Lolla et al., 2014a; 2014b). However, extending this approach to coordinated path planning is a major challenge. It may require a completely different method or a combination with one of the above-mentioned algorithms. Presently, inspired by fluid and ocean modeling, our aim is to obtain and employ governing principles and equations that lead to coordinated motions under varied flow regimes. A second challenge is how to deal with physical obstacles and dynamic forbidden regions in such coordinated planning, without increasing the computational cost. All of these challenges are addressed next.

In Section 2, we define the notation and briefly review the level-set equations for time-optimal path planning. In Section 3, we show how the approach can be augmented to treat dynamic obstacles and forbidden regions. In Section 4, we extend this approach and obtain a methodology to plan optimal coordinated paths. These results are exemplified using realistic multi-scale ocean flows in Section 5. Conclusions and future work are given in Section 6.

2. Time-optimal path planning using level-set equations

Our results on time-optimal navigation in dynamic ocean flows with moving obstacles and time-optimal coordinated formation control are based on a recent level-set approach (Lolla et al., 2014a; 2014b; 2012). These level-set equations, which can be directly solved for in ocean models, are now outlined. The presentation is limited to two dimensions; the extension to higher dimensions is straightforward.

Let $\Omega \subseteq \mathbb{R}^2$ be an open set. Starting at time $t_s(\geq 0)$, suppose a vehicle (denoted by P) moves in Ω under the influence of a bounded, Lipschitz continuous dynamic flow-field $\mathbf{V}(\mathbf{x}, t) : \Omega \times [0, \infty) \to \mathbb{R}^2$. Let $F > 0$ be the maximum speed of the vehicle relative to the flow. Let the start and end points of the vehicle be denoted by $\mathbf{y}^s$ and $\mathbf{y}^f$ respectively. The trajectory of the vehicle, denoted by $\mathbf{X}_P(t; \mathbf{y}^s, t^s)$ is governed by the kinematic relation

$$\frac{\mathrm{d}\mathbf{X}_P}{\mathrm{d}t} = F_P(t)\hat{h}(t) + \mathbf{V}(\mathbf{X}_P(t; \mathbf{y}^s, t^s), t), \quad t > t^s, \tag{1}$$

where $F_P(t)$ is the instantaneous relative speed of the vehicle that satisfies $0 \leq F_P(t) \leq F$ and $\hat{h}(t)$ is the unit vector in the steering (heading) direction. Hence, the relative velocity of the vehicle is $F_P(t)\hat{h}(t)$, and