

Path Planning for UAVs in Time-Varying Winds

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Abstract

In this paper we introduce a new approach, called *symbolic wavefront expansion*, determining both the path and the departure time minimizing the travel time of a UAV in presence of dynamic wind fields. The key idea of this approach is to manipulate functions instead of numerical values.

Introduction

Recent advances made in the field of autonomous vehicles suggest that, in a near future, Unmanned Air Vehicles (UAVs) will be more and more deployed in order to achieve various missions such as surveillance, intelligence or search and rescue. Moreover, since UAVs are generally small or slow, the impact of winds is significant, and cannot be neglected.

Specific path planning approaches have been proposed to handle winds, based on evolutionary computation (Alvarez, Caiti, & Onken 2004), wavefront expansion (Pêtrès *et al.* 2007) or optimization techniques (Zhang *et al.* 2008). These approaches determine the path taking at most profit of winds, i.e. maximize the parts of the path where the vehicle and the winds point in the same direction.

The main drawback of these approaches is that they require fixing the departure time in advance. Fixing the departure time allows knowing the state of the winds, which is necessary to evaluate the travel cost of the vehicle.

However, in many applications, the departure time may vary in a given time window. In such situations, the choice of an appropriate departure time is a critical issue: if it is improperly chosen, winds may be against the vehicle, whatever the path planned. This can be illustrated by comparing the effects of the winds to the traffic: during rush hours, whatever the route used, the travel time by car will be much more important than the one obtained after these rush hours.

That is why we introduce a new approach mixing concepts from mobile robotics (the wavefront expansion (Dorst & Trovato 1988)) and communication networks (handling time-dependent costs by manipulating functions (Orda & Rom 1990)). The resulting algorithm, that we called *symbolic wavefront expansion*, is able to determine both the path and the departure time (in a given time window), minimizing the travel time.

Problem statement

Our problem consists in finding both the path P and the departure time d^* (in a time window $[0, T]$) for an UAV, minimizing its travel time between two points A and B in a planar environment, containing space and time varying winds.

The velocity of the vehicle relative to the wind is constant (cruise speed). Winds are known through k charts denoted C_1, C_2, \dots, C_k , obtained by forecasting. Each chart is applied in the environment from $t = t_{i-1}$ to $t = t_i$.

The environment is discretized using a regular grid. Each cell X of this grid has an attribute c_X , representing the travel time required to reach X from the start point A for all possible departure times. An instance of our problem is depicted in figure 1.

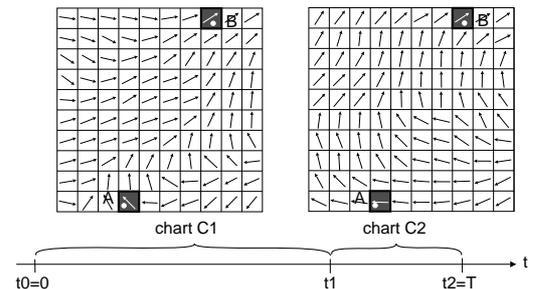


Figure 1: A path planning problem in time-varying winds, with two wind charts C_1 and C_2 .

The symbolic wavefront expansion

The wavefront expansion was first introduced in (Dorst & Trovato 1988). It consists in iteratively expanding a wavefront F from the cell A within the grid until it has reached the cell B . An expansion step consists in extracting the cell H for which the cost c_H is minimal and then propagating this cost to its neighbors. This propagation is done in two steps: (1) an evaluation step and (2) a comparison step.

In the "classical" wavefront expansion described above, the cost c_X associated to a cell X is a number. Thus, propagation steps involve numeric operations. In the symbolic wavefront expansion we propose, c_X is not a number anymore, but a function of the departure time. Therefore, propagation steps involve symbolic operations,

similarly to (Orda & Rom 1990). These operations remains computationally efficient because manipulated functions are piecewise linear.

Redefining the evaluation operator: The evaluation operation is used to compute the cost c_N of a new cell N , coming from H (already evaluated).

In the classical wavefront expansion, the cost c_N is obtained by adding travel time between H and N , given by a metric $\mathcal{M}_{H,N}$, to the cost c_H . More formally, we have $c_N = c_H + \mathcal{M}_{H,N}(c_H + d)$, where d is a fixed value representing the departure time from A .

In the symbolic wavefront expansion, d is a variable (lying in $[0, T]$) and c_N and c_H are functions of this variable. Therefore, all operations are now symbolic. It means that they operate on functions expressions rather than on numerical values. For instance, if a linear piece of c_H is defined by $d \mapsto a \cdot d + b$, then $c_H + d$ is defined by $d \mapsto (a + 1) \cdot d + b$. Moreover, since $\mathcal{M}_{H,N}$ and $c_H + d$ are two functions, the operation $\mathcal{M}_{H,N}(c_H + d)$ consists in compounding them.

Redefining the comparison operator: The comparison operation is used to choose between two concurrent sources H_0 and H_1 for a same destination N , by comparing the costs c_N^0 and c_N^1 associated to the moves $H_0 \rightarrow N$ and $H_1 \rightarrow N$.

In the classical wavefront expansion, this operation consists in comparing the two numerical values c_N^0 and c_N^1 . The predecessor H_i leading to the smallest value c_N^i will be selected to reach N .

In the symbolic wavefront expansion, this comparison is performed for all possible departure times d . By this way, we build a new function c_N defined by $d \mapsto \min \{c_N^0(d), c_N^1(d)\}$. This combination is illustrated in figure 2. For each value of d , a backpointer towards the optimal predecessor H^i (for which $c_N^i(d)$ is minimal) is stored.

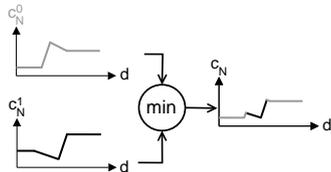


Figure 2: Our symbolic comparison operator

Building the solution:

- Optimal departure time (fig. 3):
By construction, the departure time minimizing the travel time from A to B is the minimum of the cost function c_B . Since c_B is piecewise linear, this minimum can easily be located by enumerating the pieces of c_B .
- Optimal path (fig. 4):
Once d^* is known, the optimal path is build by following backpointers stored during the cost propagation.

Implementation

The symbolic wavefront expansion has been implemented in our planner Airplan (Soulignac & Taillibert 2006). We re-

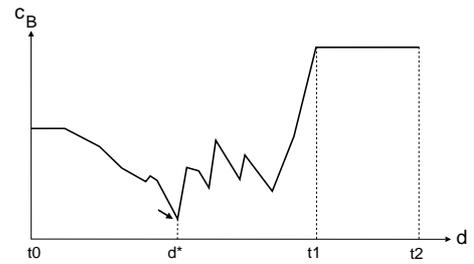


Figure 3: The cost function c_B and optimal departure time d^* for the problem of fig. 1.

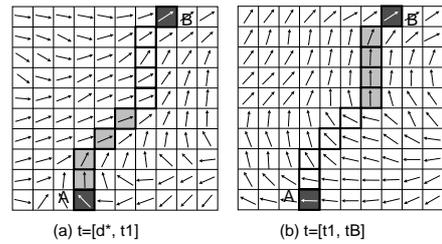


Figure 4: The optimal path for the problem of fig. 1. The departure of the robot has been delayed such that, in each chart, the robot is "pushed" by winds (grey parts).

placed the classical wavefront expansion by the symbolic one. This new version will be demonstrated during the workshop on actual wind charts.

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