Fast Algorithms for Optimal Control, Anisotropic Front Propagation and Multiple Arrivals

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Abstract

We review some recent work in fast, efficient and accurate methods to compute viscosity solutions and non-viscosity solutions to static Hamilton-Jacobi equations which arise in optimal control, anisotropic front propagation, and multiple arrivals in wave propagation. For viscosity solutions, the class of algorithms are known as "Ordered Upwind Methods", and rely on a systematic ordering inherent in the characteristic flow of information. For non-viscosity multiple arrivals, the techniques hinge on a static boundary value phase-space formulation which again can be solved through a systematic ordering.

Keywords and Phrases: Hamilton-Jacobi Equations, Fast Marching Methods, Ordered Upwind Methods.

1. Introduction

This paper reviews recent work on algorithms for static Hamilton-Jacobi equations of the form H(Du, x) = 0; the solution u depends on $x \in \mathbb{R}^n$, and boundary conditions are supplied on a subset of \mathbb{R}^n . These equations arise in such areas as wave propagation, optimal control, anisotropic front propagation, medical imaging, optics, and robotic navigation. We develop algorithms to solve these equations remarkably quickly, with the same optimal efficiency as classic algorithms for shortest paths on discrete weighted networks, but extended to continuous Hamilton-Jacobi equations.

The algorithms, which rely on a close examination of the flow of information inherent in static Hamilton-Jacobi equations, are robust, unconditionally stable without time step restriction, and efficient. They are "One-pass" schemes, in that the solution is computed at N grid points in $O(N \log N)$ steps.

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1.1. Viscosity vs. Non-Viscosity Solutions

What is meant by a solution to H(Du, x) = 0? Viscosity solutions [3] provide a unique and well-posed formulation which is linked to the unique viscosity limit of the associated smoothed equation; these are first arrivals in the propagation of information. Figure 1a shows an example from semiconductor manufacturing in which a beam whose strength is angle-dependent is used to anistropically etch away a metal surface. Figure 1b shows an optimal control problem to find the shortest exit path for a vehicle with position and direction-dependent speed.



on etching in Anisotropic Front Propagation Optimal Contro. Figure 1a Figure 1b

Figure 1: Viscosity Solutions to Static HJ Equations

The above are viscosity solutions. However, there are many cases in which later arrivals, or "non-viscosity" solutions, are desirable. Figure 2a shows the propagation of a wave inwards from a square boundary; the evolving front passes through itself and later arrivals form cusps and swallowtails as they move; Figure 2b shows multiple arrivals in geophysical wave propagation.



Figure 2: Non-viscosity solutions

Our goal is to create efficient algorithms which allow us to compute both types of solutions. In the case of viscosity solutions, algorithms are provided by the class of "Ordered Upwind Methods" developed by Sethian and Vladimirsky in [12, 13]; these methods work in physical space and construct the solution in a "One-pass" manner through a careful adherence to a causality inherent in the characteristic flow of the information. In the case of non-viscosity solution, algorithms are provided by the time-independent phase-space formulation developed by Fomel and Sethian [7], which relies on conversion of multiple arrivals into an Eulerian static boundary value problem, which can also be solved very efficiently in a "One-pass" manner which avoids all iteration through a careful ordering procedure. The remainder of this paper is devoted to describing these two classes of algorithms and providing a few computational results.

2. Fast Methods for Viscosity Solutions

We first discuss "Ordered Upwind Methods" introduced in [12] for computing viscosity solutions.

2.1. Discrete Control: Dijkstra's Method

Consider a discrete optimal trajectory problem on a network. Given a network and a cost associated with each node, the global optimal trajectory is the most efficient path from a starting point to some exit set in the domain. Dijkstra's classic algorithm [4] computes the minimal cost of reaching any node on a network in $O(N \log N)$ operations. Since the cost can depend on both the particular node, and the particular link, Dijkstra's method applies to both *isotropic* and *anisotropic* control problems. The distinction is minor for discrete problems, but significant for continuous problems. Dijkstra's method is a "one-pass" algorithm; each point on the network is updated a constant number of times to produce the solution. This efficiency comes from a careful analysis of the direction of information propagation and stems from the optimality principle.

We briefly summarize Dijsktra's method, since the flow logic will be important in explaining our Ordered Upwind Methods. For simplicity, imagine a rectangular grid of size h, where the cost $C_{ij} > 0$ is given for passing through each grid point $x_{ij} = (ih, jh)$. Given a starting point, the minimal total cost U_{ij} of arriving at the node x_{ij} can be written in terms of the minimal total cost of arriving at its neighbors:

$$U_{ij} = \min\left(U_{i-1,j}, U_{i+1,j}, U_{i,j-1}, U_{i,j+1}\right) + C_{ij}.$$
(2.1)

To find the minimal total cost, Dijkstra's method divides mesh points into three classes: Far (no information about the correct value of U is known), Accepted (the correct value of U has been computed), and Considered (adjacent to Accepted). The algorithm proceeds by moving the smallest Considered value into the Accepted set, moving its Far neighbors into the Considered set, and recomputing all Considered neighbors according to formula 2.1. This algorithm has the computational complexity of $O(N \log(N))$; the factor of $\log(N)$ reflects the necessity of maintaining a sorted list of the *Considered* values U_i to determine the next *Accepted* mesh point. Efficient implementation can be obtained using heap-sort data structures.

2.2. Continuous Control: Ordered Upwind Methods

Consider now the problem of continuous optimal control; here, the goal is to find the optimal path from a starting position to an exit set. Dijkstra's method does not converge to the continuous solution as the mesh becomes finer and finer, since (see [11]) it produces the solution to the partial differential equation $\max(|u_x|, |u_y|) =$ h * C, where h is the grid size. As h goes to zero, this does not converge to the solution of the continuous Eikonal problem given by $|u_x^2 + u_y^2|^{1/2} = C$ Thus, Dikstra's method cannot be used to obtain a solution to the continuous problem.

2.2.1. Ordered Upwind Solvers for Continuous Isotropic Control

In the case of isotropic cost functions in which the cost depends only on position and not on direction, two recent algorithms, first Tsitsiklis's Method [16] and then Sethian's Fast Marching Method [10] have been introduced to solve the problems with the same computational complexity as Dijkstra's method. Both methods exploit information about the flow of information to obtain this efficiency; the causality allows one to build the solution in increasing order, which yields the Dijkstra-like nature of the solutions. Both algorithms result from a key feature of Eikonal equations, namely that their characteristic lines coincide with the gradient lines of the viscosity solution u(x); this allows the construction of one-pass algorithms. Tsitsiklis' algorithm evolved from studying isotropic min-time optimal trajectory problems, and involves solving a minimization problem to update the solution. Sethian's Fast Marching Method evolved from studying isotropic front propagation problems, and involves an upwind finite difference formulation to update the solution. Each method starts with a particular (and different) coupled discretization and each shows that the resulting system can be decoupled through a causality property. We refer the reader to these references for details on ordered upwind methods for Eikonal equations, as well as [13] for a detailed discussion about the similarities and differences between the two techniques.

2.2.2. Ordered Upwind Solvers for Continuous Anisotropic General Optimal Control

Consider now the full continuous optimal control problem, in which the cost function depends on both position and direction. In [12, 13], Sethian and Vladimirsky built and developed single-pass "Ordered Upwind Methods" for any continuous optimal control problem. They showed how to to produce the solution U_i by recalculating each U_i at most r times, where r depends only the equation and the mesh structure, but not upon the number of mesh points.

Building one-pass Dijkstra-like methods for general optimal control is considerably more challenging than it is for the Eikonal case, since characteristics no longer coincide with gradient lines of the viscosity solution. Thus, characteristics and gradient lines may in fact lie in different simplexes. This is precisely why both Sethian's Fast Marching Method and Tsitsiklis' Algorithm cannot be directly applied in the anisotropic (non-Eikonal) case: it is no longer possible to de-couple the system by computing/accepting the mesh points in the ascending order.

The key idea introduced in [12, 13] is to use the location anisotropy of the cost function to limit of the number of points on the accepted front that must be examined in the update of each Considered point. Consider the anisotropic mintime optimal trajectory problems, in which the speed of motion depends not only on position but also on direction. The value function u for such problems is the viscosity solution of the static Hamilton-Jacobi-Bellman equation

$$\max_{a \in S_1} \left\{ (\nabla u(x) \cdot (-a)) f(a, x) \right\} = 1, \quad x \in \Omega, \\ u(x) = q(x), \qquad \qquad x \in \partial\Omega.$$
(2.2)

In this formulation, a is the unit vector determining the direction of motion, f(a, x) is the speed of motion in the direction a starting from the point $x \in \Omega$, and q(x) is the time-penalty for exiting the domain at the point $x \in \partial\Omega$. The maximizer a corresponds to the characteristic direction for the point x. If f does not depend on a, Eqn. 2.2 reduces to the Eikonal equation, see [1].

Now, define the anisotropy ratio F_1/F_2 , where $0 < F_1 \leq f(a, x) \leq F_2 < \infty$. In [13], two key lemmas were proved:

- Lemma 1. Consider the characteristic passing through $\bar{x} \in \Omega$ and level curve u(x) = C, where $q_{max} < C < u(\bar{x})$. The characteristic intersects that level set at some point \tilde{x} . If \bar{x} is distance d away from the level set then $\|\tilde{x} \bar{x}\| \leq d\frac{F_2}{F_1}$.
- Lemma 2. Consider an unstructured mesh X of diameter h on Ω . Consider a simple closed curve Γ lying inside Ω with the property that for any point xon Γ , there exists a mesh point y inside Γ such that ||x - y|| < h. Suppose the mesh point \bar{x}_i has the smallest value $u(\bar{x}_i)$ of all of the mesh points inside the curve. If the characteristic passing through \bar{x}_i intersects that curve at some point \tilde{x}_i then $||\tilde{x}_i - \bar{x}_i|| \leq h \frac{F_2}{F_1}$.

Thus, one may use the anisotropy ratio to exclude a large fraction of points on the Accepted Front in the update of any Considered Point; the size of this excluded subset depends on the anisotropy ratio. Building on these results, a fast, Dijkstralike method was constructed. As before, three of mesh points classes are used. The AcceptedFront is defined as a set of Accepted mesh points, which are adjacent to some not-yet-accepted mesh points. Define the set AF of the line segments x_jx_k , where x_j and x_k are adjacent mesh points on the AcceptedFront, such that there exists a Considered mesh point x_i adjacent to both x_j and x_k . For each Considered mesh point x_i one defines the part of AF "relevant to x_i ":

$$NF(x_i) = \left\{ (x_j, x_k) \in AF \mid \exists \tilde{x} \text{ on } (x_j, x_k) \text{ s.t. } \|\tilde{x} - x_i\| \le h \frac{F_2}{F_1} \right\}.$$

We will further assume that some consistent upwinding update formula is available: if the characteristic for x_i lies in the simplex $x_i x_j x_k$ then $U_i = K(U_j, U_k, x_i, x_j, x_k)$. For the sake of notational simplicity we will refer to this value as $K_{j,k}$.

- 1. Start with all mesh points in $Far(U_i = \infty)$.
- 2. Move the boundary mesh points $(x_i \in \delta\Omega)$ to Accepted $(U_i = q(x_i))$.
- 3. Move all the mesh points x_i adjacent to the boundary into Considered and evaluate the tentative value of $U_i = \min_{(x_j, x_k) NF(x_i)} K_{j,k}$.
- 4. Find the mesh point x_r with the smallest value of U among all the Considered.
- 5. Move x_r to Accepted and update the AcceptedFront.
- 6. Move the Far mesh points adjacent to x_r into Considered.
- 7. Recompute the value for all the Considered x_i within the distance $h \frac{F_2}{F_1}$ from x_r . If less than the previous tentative value for x_i then update U_i .
- 8. If *Considered* is not empty then goto 4).

2.2.3. Analysis and Results

This is a "single-pass" algorithm since the maximum number of times each mesh point can be re-evaluated is bounded by the number of mesh points in the $h\frac{F_2}{F_1}$ neighborhood of that point; the method formally has the computational complexity of $O((\frac{F_2}{F_1})^2 M \log(M))$. Convergence of the method to the viscosity solution is proved in [13], and depends on the upwinding update formula $U_i = K(U_j, U_k, x_i, x_j, x_k)$.

As an example, taken from [12], we compute the geodesic distance on the manifold $g(x, y) = .9 \sin(2\pi x) \sin(2\pi y)$ from the origin. This can be shown to be equivalent to solving the static Hamilton-Jacobi equation

$$\|\nabla u(\boldsymbol{x})\|F\left(\boldsymbol{x}, \frac{\nabla u(\boldsymbol{x})}{\|\nabla u(\boldsymbol{x})\|}\right) = 1,$$
(2.3)

with speed function F given by $F(x, y, \omega) = \sqrt{\frac{1+g_y^2 \cos^2(\omega) + g_x^2 \sin^2(\omega) - g_x g_y \sin(2\omega)}{1+g_x^2 + g_y^2}}$

where ω is the angle between $\nabla u(x, y)$ and the positive direction of the *x*-axis. The anisotropy is substantial, since the dependence of *F* upon ω can be pronounced when ∇g is relatively large. Equidistant contours are shown on the left in Figure 3.



Figure 3: Left: Anistropic Front Propagation Right: Arrival Paths

3. Fast Methods for Multiple Arrivals

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3.1. Computing Multiple Arrivals

We now consider the problem of multiple arrivals. As an example, consider the two-dimensional Eikonal equation

$$|\nabla u|F(x,y) = 0 \tag{3.1}$$

with F(x, y) given. We imagine a computational domain and a source point, as shown on the right in Figure 3. Suppose the goal is to determine the arrival time and path to each point in the interior from the source point. Here, we are interested not only in the first arrival, but all later arrivals as well.

One popular approach to computing multiple arrivals is to work in phase space, in which the dimensionality of the problem is increased from physical space to include the derivative of the solution as well. There are two approaches to computing these multiple arrivals through a phase space formulation. One is a Lagrangian (ray tracing) approach, in which the phase space characteristic equations are integrated, often from a source point, resulting in a Lagrangian structure which fans out over the domain. Difficulties can occur in either in low ray density zones where there are very few rays or near caustics where rays cross. The other is an Eulerian description of the problem, in either the physical domain or phase space. In recent years, this has led to many fascinating and clever Eulerian PDE-based approaches to computing multiple arrivals, see, for example, [15, 14, 9, 5, 2]. We note that the regularity of the phase space has been utilized previously in theoretical studies on the asymptotic wave propagation [8]. The above phase space approaches to solving for multiple arrivals have two characteristics in common:

- A phase space formulation increases the dimensionality of the problem. In two physical dimensions, the phase space formulation requires three dimensions; in three physical dimensions, the phase space formulation is in five dimensions.
- Given particular sources, the problem is solved with those source location(s) as initial data. Different sources requires re-solving the entire problem.
- The problem is cast as an initial value partial differential equation, and is evolved in time. Time step considerations in regions of high velocity play a role in the stability of the underlying scheme.

3.2. A Boundary Value Formulation

Fomel and Sethian [7] take a different approach. A set of time-independent "Escape Equations" are derived, each of which is an Eulerian boundary value partial differential equation in phase space. Together, they give the exit time, location and derivative of all possible trajectories starting from all possible interior points. Thus, the particular choice of sources is reduced to post-processing. The computational speed depends on whether one wants to obtain results for all possible boundary conditions, or in fact only for a particular subset of possibilities.

3.2.1. Liouville Formulation

Briefly (see [7] for details) begin with the static Hamilton-Jacobi equation

$$H(x,\nabla u) = 0, (3.2)$$

and write the well-known characteristic equations in phase space (x, p), where p corresponds to ∇u (see, for example, [6]). The characteristics must obey

$$\frac{dx}{d\sigma} = \nabla_p H; \qquad \qquad \frac{dp}{d\sigma} = -\nabla_x H. \tag{3.3}$$

Differentiating the function $u(x(\sigma))$, we obtain an additional equation for transporting the function u along the characteristics:

$$\frac{du}{d\sigma} = \nabla u \cdot \frac{dx}{d\sigma} = p \cdot \nabla_p H. \tag{3.4}$$

Eqns. 3.3,3.4 can be initialized at $\sigma = 0$: $x(0) = x_0$, $p(0) = p_0$, u(0) = 0.

One can now convert the phase space approach into a set of Liouville equations. To simplify notation, we denote the phase-space vector (x, p), by y, the right-hand side of system given in Eqn. 3.3 by vector function R(y), and the right-hand side of Eqn. 3.4 by the function r(y). In this notation, the Hamilton-Jacobi system is

$$\frac{\partial y(y_0,\sigma)}{\partial \sigma} = R(y); \qquad \frac{\partial u(y_0,\sigma)}{\partial \sigma} = r(y), \tag{3.5}$$

and is initialized at $\sigma = 0$ as $y = y_0$ and u = 0. This system satisfies

$$\frac{\partial y(y_0,\sigma)}{\partial \sigma} = \nabla_0 y \, R(y_0) \,, \tag{3.6}$$

and the transported function u satisfies the analogous equation

$$\frac{\partial u(y_0,\sigma)}{\partial \sigma} = \nabla_0 u \, R(y_0) + r(y_0) \,, \tag{3.7}$$

where ∇_0 denotes the gradient with respect to y_0 . These are the Liouville equations.

3.2.2. Formulation of Escape Equations

The key idea in [7] is as follows. Assume a closed boundary $\partial \mathcal{D}$ in the y space that is crossed by every characteristic trajectory originating in $y_0 \in \mathcal{D}$. This defines for every y_0 the function $\sigma = \hat{\sigma}(y_0)$ of the first crossing of the corresponding characteristic with $\partial \mathcal{D}$. Now introduce a differentiable function $\Gamma(y)$ that identifies the boundary, that is, $\Gamma(y) = 0$. In particular, we then have that $\Gamma(y(y_0, \hat{\sigma}(y_0)) = 0$. One can then differentiate with respect to the initial condition y_0 to obtain an escape equation for the parameter $\hat{\sigma}$. Similarly, one can derive escape equations for the position and value, yielding the full set of

EscapeEquations
$$1 + \nabla_0 \hat{\sigma} \cdot R(y_0) = 0$$

 $\nabla_0 \hat{y} R(y_0) = 0$
 $\nabla_0 \hat{u} \cdot R(y_0) + r(y_0) = 0$
(3.8)

3.3. Fast Solution of Escape Equations

Summarizing, rather than compute in physical space, we derive boundary value Escape equations in phase space y = (x, p). All time step considerations are avoided, and one can compute all the arrivals from all possible sources simultaneously. This Eulerian formulation means that the entire domain is covered, even quiet slow zones.

Finally, and most importantly, a constructive, "One-pass" algorithm, similar to the one presented for viscosity solutions, can be designed. Exit time, position, and derivative at the boundary form boundary conditions. We can then systematically march the solution inwards in phase space from the boundary, constructing the solution through an ordering sequence based on the characteristics that ensures computational phase space mesh points need not be revisited more than once.

Consider a square boundary as an example, and suppose we wish to find the time $\hat{u}(x, z, \theta)$ at which a ray leaving the initial point (x, z) inside the square, initially moving in direction θ , hits the boundary. We assume that the slowness field n(x, z) is given. First, note that the set $\hat{u}(x, z, \theta) = T$, drawn in x, z, θ space, gives the set of all initial positions and directions which reach the boundary of the square at time T. By the uniqueness of characteristics, the set of all points parameterized by T and given by $\hat{U}(T) = \{x, z, \theta \mid \hat{u}(x, z, \theta) = T\}$ sweep out the solution space. Figure 3.3.a shows the solution surfaces $\hat{u}(x, z, \theta)$ for the collapsing square.

Details on the exact algorithm are given in [7]. As demonstration (see [7]), in Figure 3.3.b, the top pair shows all the arrivals starting from a source at the center of the top wall, together with the slowness field on the right (darker is slower). The bottom pair shows the first arrival and on the amplitude of the displayed arrival (the lighter the tone, the more amplitude).

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Fig.3.3.b: All vs. First Arrivals

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