# Path Planning with Fast Marching Methods 

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## Basic Path Planning

- Find the optimal path $p(s)$ to a target (or from a source)
- Inputs
- Cost to pass through each state in the state space
- Set of targets or sources (provides boundary conditions)



## Dynamic Programming Principle

$$
V(x)=\min _{y \in N(x)}[V(y)+c(y \rightarrow x)]
$$

- Value function $V(x)$ is "cost to go" from $x$ to the nearest target
- $V(x)$ at a point $x$ is the minimum over all points $y$ in the neighborhood $N(x)$ of the sum of
- the cost $V(y)$ at point $y$
- the cost $c(y \rightarrow x)$ to travel from $y$ to $x$
- Dynamic programming applies if
- Costs are additive
- Subsets of feasible paths are themselves feasible
- Concatenations of feasible paths are feasible


## Eikonal Equation

$$
\|\nabla V(x)\|=c(x)
$$

- Value function is viscosity solution of Eikonal equation
- Dynamic Programming Principle applies to Eikonal Equation
- Fast Marching Method: a continuous Dijkstra's algorithm
- Node update equation is consistent with continuous PDE (and numerically stable)
- Nodes are dynamically ordered so that each is visited a constant number of times


## Path Generation

- Optimal path $p(s)$ is found by gradient descent
- Value function $V(x)$ has no local minima, so paths will always terminate at a target

$$
\frac{d p}{d s}=\frac{\nabla V(x)}{\|\nabla V(x)\|}
$$



## Demanding Example? No!



## Constrained Path Planning

- Input includes multiple cost functions $c_{i}(x)$
- Possible goals:
- Find feasible paths given bounds on each cost
- Optimize one cost subject to bounds on the others
- Given a feasible/optimal path, determine marginals of the constraining costs



## Path Integrals

- To determine if path $p(t)$ is feasible, we must determine

$$
P_{i}(x)=\int_{0}^{T} c_{i}(p(s)) d s, \text { where }\left\{\begin{array}{l}
p(0)=\text { target } \\
p(T)=x
\end{array}\right.
$$

- If the path is generated from a value function $V(x)$, then path integrals can be computed by solving the PDE

$$
\nabla P_{i}(x) \cdot \nabla V(x)=c_{i}(x) c(x)
$$

- The computation of the $P_{i}(x)$ can be integrated into the FMM algorithm that computes $V(x)$


## Pareto Optimality

- Consider a single point $x$ and a set of costs $c_{i}(x)$
- Path $p_{m}$ is unambiguously better than path $p_{n}$ if

$$
P_{i}\left(x ; p_{m}\right) \leq P_{i}\left(x ; p_{n}\right) \text { for all } i
$$

- Pareto optimal surface is the set of all paths for which there are no other paths that are unambiguously better



## Exploring the Pareto Surface

- Compute value function for a convex combination of cost functions
- For example, let $c(x)=\lambda c_{1}(x)+(1-\lambda) c_{2}(x), \lambda \in[0,1]$
- Use FMM to compute corresponding $V(x)$ and $P_{i}(x)$
- Constructs a convex approximation of the Pareto surface for each point $x$ in the state space



## Constrained Path Planning Example

- Plan a path across Squaraguay
- From Lowerleftville to Upper Right City
- Costs are fuel (constant) and threat of a storm

Weather cost (two views)



## Weather and Fuel Constrained Paths

| line type | minimize <br> what? | fuel <br> constraint | fuel <br> cost | weather <br> cost |
| :---: | :---: | :---: | :---: | :---: |
| $-=-=-$ | fuel | none | 1.14 | 8.81 |
| - | weather | 1.3 | 1.27 | 4.55 |
| - | weather | 1.6 | 1.58 | 3.03 |
| $-=-=-$ | weather | none | 2.69 | 2.71 |



## Pareto Optimal Approximation

- Cost depends linearly on number of sample $\lambda$ values
- For $201^{2}$ grid and $401 \lambda$ samples, execution time 53 seconds



## More Constraints

- Plan a path across Squaraguay
- From Lowerleftville to Upper Right City
- There are no weather stations in northwest Squaraguay
- Third cost function is uncertainty in weather

Uncertainty cost (two views)


## Three Costs

| line <br> type | minimize <br> what? | fuel <br> constraint | weather <br> constraint | fuel <br> cost | weather <br> cost | uncertainty <br> cost |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $-=-=-$ | fuel | none | none | 1.14 | 8.81 | 1.50 |
| $-=-=-$ | weather | none | none | 2.69 | 2.71 | 5.83 |
| $-=---$ | uncertainty | none | none | 1.17 | 8.41 | 1.17 |
| - | weather | 1.6 | none | 1.60 | 3.02 | 2.84 |
| - | weather | 1.3 | none | 1.30 | 4.42 | 2.58 |
| - | uncertainty | 1.3 | 6.0 | 1.23 | 5.84 | 1.23 |



## Pareto Surface Approximation

- Cost depends linearly on number of sample $\lambda$ values
- For $201^{2}$ grid and $101^{2} \lambda$ samples, execution time 13 minutes

For Destination $=[0.9,0.9]$


Weather Cost
Fuel Cost

## Three Dimensions

| line type | minimize <br> what? | fuel <br> constraint | fuel <br> cost | weather <br> cost |
| :---: | :---: | :---: | :---: | :---: |
| ---- | fuel | none | 1.14 | 3.54 |
| --- | weather | none | 1.64 | 1.64 |
| - | weather | 1.55 | 1.55 | 2.00 |




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## Constrained Example

- Plan path to selected sites
- Threat cost function is maximum of individual threats
- For each target, plan 3 paths
- minimum threat, minimum fuel, minimum threat (with fuel $\leq 300$ )




## Fast Enough?

- Platform details
- 2 GHz Mobile Pentium 4, 1 GB memory, Windows XP Pro
- Value function by compiled C++
- Path generation by interpreted m-file integration

| Value Function <br> (single objective) |  |  |
| ---: | ---: | ---: |
| dim | grid size | time (s) |
| 2 | $101^{2}$ | 0.04 |
|  | $201^{2}$ | 0.10 |
|  | $401^{2}$ | 0.43 |
|  | $801^{2}$ | 1.87 |
|  | $1601^{2}$ | 9.33 |
| 3 | $51^{3}$ | 0.90 |
|  | $101^{3}$ | 9.78 |
|  | $201^{3}$ | 94.91 |
| 4 | $51^{4}$ | 166.76 |


| Path Generation <br> (25 random targets) |  |  |  |
| ---: | ---: | ---: | ---: |
| dim | grid size | mean (s) | $\sigma$ |
| 2 | $101^{2}$ | 0.57 | 0.32 |
|  | $201^{2}$ | 0.62 | 0.38 |
|  | $401^{2}$ | 0.72 | 0.51 |
|  | $801^{2}$ | 0.82 | 0.60 |
|  | $1601^{2}$ | 1.05 | 0.75 |
| 3 | $51^{3}$ | 0.92 | 0.38 |
|  | $101^{3}$ | 0.89 | 0.49 |
|  | $201^{3}$ | 0.95 | 0.48 |
| 4 | $51^{4}$ | 1.62 | 0.57 |

## Grid Refinement

- As resolution improves, the approximation converges to the analytically optimal path for almost every destination point
- little qualitative difference if cost function features are resolved



## Path Generation Times

- Platform details
- 2 GHz Mobile Pentium 4, 1 GB memory, Windows XP Pro
- Value function by compiled C++
- Path generation by interpreted m-file integration
- Total cost includes cost function generation, PDE and ODE solves and plotting all the figures

| 2D cost per sample |  |  |
| ---: | ---: | ---: |
| $\boldsymbol{N}$ | time (s) <br> per $\boldsymbol{\lambda}$ | ratio |
| 51 | 0.01 |  |
| 101 | 0.04 | 3.24 |
| 201 | 0.13 | 3.76 |
| 401 | 0.55 | 4.20 |
| 801 | 2.44 | 4.41 |


| 3D cost per sample |  |  |
| ---: | ---: | ---: |
| $\boldsymbol{N}$ | time (s) <br> per $\lambda$ | ratio |
| 51 | 1.27 |  |
| 101 | 12.66 | 9.99 |
| 201 | 125.46 | 9.91 |


| Total cost for each example |  |  |  |  |
| ---: | ---: | :---: | :---: | ---: |
| $\boldsymbol{d}$ | $\boldsymbol{k}$ | $\boldsymbol{N}$ | $\Delta \boldsymbol{\lambda}$ | time $(\mathrm{m})$ |
| 2 | 2 | 201 | 0.005 | 0.5 |
| 2 | 3 | 101 | 0.020 | 1.0 |
| 3 | 2 | 101 | 0.010 | 22.3 |

