

# Best practices for A\* on grids

Chris Rayner

February 20, 2017



## Description

This document describes ways to improve A\*, focusing on pathfinding on four- and eight-connected grids. It's pitched at hobbyists and anyone looking for ways to make an existing implementation a bit faster.

Some accompanying [example code](#) is available in C++.

## Contributing

If you have any corrections or contributions – both much appreciated – feel free to get in touch or simply make a pull request.

## Preliminaries

Forgoing a complete description, recall that A\* is essentially a loop that expands a list of *open* states that reach toward a goal state. Each iteration of the A\* loop expands the *open list* with the neighbors of a state already on the open list. The open state *i* that gets chosen is one with the lowest *f* value:

$$f_i = g_i + h_i$$

which is an estimate of the cost of a path going through *i* and continuing to the goal. Here *g<sub>i</sub>* is the cost of the cheapest path to state *i* that A\* has generated so far, and *h<sub>i</sub>* is an efficiently computed *heuristic estimate* for the cost to get from *i* to the goal.

(For further detail, visit the resources at the end of the document.)

## Heuristics and move costs

### Avoid floating point arithmetic

Prefer integral data types wherever possible. This is not only faster but helps to avoid the numerical imprecision that can confuse debugging attempts.

### Use a non-overestimating heuristic

Heuristics that don't overestimate are called *admissible*. A\* recovers an optimal (cheapest) path when its heuristic is admissible. A good, admissible grid heuristic is the "distance" between two states assuming no obstacles.

#### On a 4-connected grid

The distance between two states on a 4-connected grid, assuming no obstacles, is the **rectilinear** (or **L1-norm** or **Manhattan**) distance:

$$h_i = C * (\Delta x + \Delta y)$$

where  $\Delta x$  and  $\Delta y$  are absolute distances between  $i$  and the goal along the  $x$  and  $y$  axes and  $C$  is the cost to take a cardinal move, which may as well be 1.

#### On an 8-connected grid

When pathfinding on an 8-connected grid, use the **octile** heuristic:

$$h_i = \begin{array}{ll} C * \Delta x + B * \Delta y & \text{if } \Delta x > \Delta y \\ C * \Delta y + B * \Delta x & \text{else} \end{array}$$

where  $B = D - C$  with  $C$  being the cost to take a cardinal move and  $D$  being the cost to take a diagonal move. (See [example code](#).)

Note the octile heuristic can be written without a conditional (albeit with an absolute value), which may help improve instruction level parallelism:

$$h_i = (E * \text{abs}(\Delta x - \Delta y) + D * (\Delta x + \Delta y)) / 2$$

where  $E = 2 * C - D$ . You can see how this simplifies further, without floating point arithmetic, if both  $D$  and  $E$  are even. (See [example code](#).)

### Choose cardinal/diagonal move costs carefully

On an 8-connected grid, the cost of a single diagonal move ( $D$ ) relative to the cost of a cardinal move ( $C$ ) not only affects the appearance of the paths A\* generates, but also its efficiency.

### Avoid same-cost diagonal and cardinal moves

When the entity can move cardinally *or* diagonally once per time-step, the instinct is to tell A\* that cardinal and diagonal moves cost the same (e.g.,  $C = D = 1$ ). While technically true, this increases the number of unique optimal paths across the grid; A\* is more efficient when it has fewer options.

### Ensure $C < D < 2C$

If a diagonal move costs *less* than a cardinal move, A\* prefers zigzagging paths. If a diagonal move costs more than *two* cardinal moves, A\* prefers rectilinear paths like you'd see on a 4-connected grid. Paths tend to look best when the costs lie between these two extremes.

### Use high-performing move costs

The following cost structures work well in practice. Results can vary depending on the obstacles in the grid, so test before using.

$D = 99, C = 70$  If you prefer a diagonal move to cost `sqrt(2)` relative to a cardinal move, try  $D = 99$  and  $C = 70$ . This close approximation helps to avoid floating point arithmetic.

$D = 3, C = 2$  This is still close to a  $D/C$  ratio of `sqrt(2)` and remains integral. Moreover, if  $h_i$  is admissible but non-integral for whatever reason, then its [ceiling](#) is admissible and can be used instead. Nathan Sturtevant showed me this when we wrote [Euclidean Heuristic Optimization](#) (Rayner, Bowling, Sturtevant), and it made a noticeable difference.

$D = 99, C = 50$  This gives something close to rectilinear costs but retains a preference for diagonal moves over pairs of cardinal moves. On average this keeps the size of the open list smaller, but it can also increase state expansions. Usually it is noticeably faster.

## Implementing the open list

### Use a binary heap

... and implement the heap using an array.

This is enormously important on large grids, but admittedly less important for small grids – on the order of a couple thousand states in optimized C++. On grids with few obstacles, maintaining the heap might be more expensive than linear scans of the open list. (See [example code](#).)

## Break ties in favor of path depth

It is common for more than one state on the open list to have the lowest  $f$  cost. When this is the case it's better to make A\* focus on deep solutions rather than a breadth of shallow solutions by tie-breaking on larger  $g$  values. My Ph.D. co-supervisor Nathan Sturtevant created [a video that demonstrates this](#). (See [example code](#).)

## Avoid recomputing heuristics

To help keep the open list sorted, an implementation of A\* might store the  $f_i$  and  $g_i$  values for every open state  $i$ . And since  $f_i = g_i + h_i$ , the value of  $h_i$  can always be recovered as  $h_i = f_i - g_i$  for any open state  $i$ . Using these stored values (a form of [memoization](#)) can be less expensive than recomputing  $h_i$ .

For instance, suppose  $i$  is on the open list with  $f$  and  $g$  values of  $f_{\text{current}}$  and  $g_{\text{current}}$ . Then A\* iterates to a cheaper path to  $i$  with a cost of  $g_{\text{new}}$ . The corresponding value  $f_{\text{new}}$  can be determined *without* making another call to the heuristic function:

$$f_{\text{new}} = g_{\text{new}} + f_{\text{current}} - g_{\text{current}}$$

(See [example code](#).)

## Consider Fringe Search

[Fringe Search](#) is a close cousin of A\* that takes a different approach to growing and maintaining the open list. The implementation is quite similar to A\*, and most of the points in this document also apply to Fringe Search, such as choosing a good heuristic, the choice of diagonal vs. cardinal move costs, and even the use of memoized heuristic values. (See [example code](#).)

With compiler optimizations on, Fringe Search is slower than A\*, albeit only if the methods in this document are applied. But with compiler optimizations off, Fringe Search can be faster than A\*. It's reasonable to *predict* that Fringe Search might be the faster choice in interpreted scripting languages...

## Additional Resources

[Patrick Lester's A\\* for beginners](#) A good starting point.

[Nathan Sturtevant's movingai.com](#) Benchmark problems, tutorials, and videos covering fundamental and advanced topics.

**Dijkstra Maps** Dijkstra Maps have also been called "differential heuristics", "ALT heuristics", or "Lipschitz embeddings". We looked at smart ways to set these heuristics up in [Subset Selection of Search Heuristics](#) (Rayner, Sturtevant, Bowling) but this article describes some extremely novel ways to use these mappings to control game entities.

**Amit Patel's variants of A\*** A listing of some alternatives to A\*.

**A\* on Wikipedia** Wikipedia gives a thorough description of A\*.