Regarding Jump Point Search and Subgoal Graphs

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Abstract

In this paper, we define Jump Point Graphs (JP), a preprocessing-based path-planning technique similar to Subgoal Graphs (SG). JP allows for the first time the combination of Jump Point Search style pruning in the context of abstraction-based speedup techniques, such as Contraction Hierarchies. We compare JP with SG and its variants and report new state-of-the-art results for grid-based pathfinding.

Introduction

Subgoal Graphs (SG) [Uras et al., 2013] and Jump Point Search (JPS) [Harabor and Grastien, 2011] are two popular and successful symmetry-breaking algorithms for optimal pathfinding on grid maps. Similar in spirit, these methods proceed quite differently in practice, and the relationship between them, in terms of strengths and weaknesses, has not been well understood. We address this gap in the literature with a new graph-theoretic description of JPS and a direct comparative analysis with SGs.

Our first result shows that JPS, like SG, connects pairs of vertices to one another using a direct reachability relation. Moreover, when pairs of vertices are not direct reachable, JPS guarantees that the path is covered by a distinguished set of vertices, namely, the set of all jump points. One disadvantage of JPS, compared to SG, is its dependence on grid-scanning and target-detection operations. JPS performs these operations repeatedly during vertex expansions, and their necessity complicates the integration of JPS with in-principle orthogonal speedup techniques.

Our second result is to overcome these limitations by extracting a graph of all jump points. The new algorithm — Jump Point Graphs (JP) — has the same strong symmetry-breaking properties as Jump Point Search but only refers to the input grid while inserting the start and target.

Our third result is an empirical evaluation that shows JP can be fruitfully combined with a variety of orthogonal speedup techniques, including bi-directional search and Contraction Hierarchies [Geisberger et al., 2008]. We also compare JP and a number of variants against leading methods from the literature, including SG. We find that JP can significantly reduce the average number of vertex expansions and also average runtime on some popular grid benchmarks.

Preliminaries and Notation

We consider shortest path search on an 8-neighbour grid graph \( G = (V, E) \) constructed from a grid map \( M \). Each cell \( n \in M \) is marked as blocked or unblocked. There are 8 available move actions \( \vec{v} \) (equiv. directions), which serve to transition the search from one cell to the next. Straight moves cost 1 and diagonal moves \( \sqrt{2} \). A move \( \vec{v} \) from a cell \( n \) to \( n' \) is unblocked (that is, \((n, n') \in E) \) iff \( n \) and \( n' \) are adjacent unblocked cells and, if \( \vec{v} \) is diagonal, then there is no blocked cell adjacent to both \( n \) and \( n' \) (no-corner-cutting constraint).

We say that a diagonal direction \( \vec{d} \) results from combining two cardinal directions; i.e. \( \vec{d} = \vec{v}_1 \times \vec{v}_2 \). Directions \( \vec{v}_1 \) and \( \vec{v}_2 \) are perpendicular, written \( \vec{v}_1 \perp \vec{v}_2 \), when the angle between them is a right angle. We also use the algebra \( n' = n + k_1 \times \vec{v}_1 + k_2 \times \vec{v}_2 \) with \( k_1 \) and \( k_2 \) as integers, to say that cell \( n' \) is reached from cell \( n \) with \( k_1 \) moves in direction \( \vec{v}_1 \) followed by \( k_2 \) moves in direction \( \vec{v}_2 \). We sometimes refer to cardinal directions by name: \( U(p), D(own), L(eft), \) and \( R(right) \).

A path \( \pi = (n_1 = s, \ldots, n_k = t) \) is an ordered sequence of cells from a distinguished cell called the start = \( s \) to a distinguished cell called the target = \( t \) such that there exists a valid move to connect every pair of adjacent cells on the path. When discussing paths, we sometimes refer to their valid continuations. A continuation is a move \( \vec{v} \) whose application extends the path by one or more cells. For example, \( \pi + k \times \vec{v} \) extends path \( \pi \) with \( k \) moves in direction \( \vec{v} \).

We refer to the (8-neighbor) grid graph constructed from \( M \) by assuming that all cells are unblocked as freespace. We refer to a shortest path \( \pi \) in freespace as a freespace-shortest path, and say that \( \pi \) is unblocked (on \( G \)) iff it is also a path on \( G \). We use a heuristic function \( h \) to measure distances in freespace, also referred to as the Octile distance heuristic.

Subgoal Graphs

Subgoal Graphs [Uras et al., 2013; Uras and Koenig, 2017] (SGs) is the name of an abstraction-based algorithm developed for fast and optimal pathfinding in directed weighted graphs. During an offline preprocessing step, a distinguished set of vertices, known as subgoals, are identified. Each subgoal appears as a vertex in an eponymous SG, and each edge in an SG corresponds to a shortest graph path. However, edges are only added to the SG between pairs of subgoals that satisfy a given reachability relation.
We now adapt definitions from [Uras and Koenig, 2017]:

**Definition 1.** A reachability relation on $G = (V, E)$ is a relation $R \subseteq V \times V$ that satisfies:

1. $\forall s \in V, (s, s) \in R$
2. $\forall (s, t) \in E, (s, t) \in R$ (edge property)

**Definition 2.** $S \subseteq V$ is an $R$-shortest-path-cover (R-SPC) on $G$ iff, for all $s, t \in V$, if $(s, t) \notin R$, then at least one shortest $s$-$t$ path on $G$ passes through some $v \in S$.

**Definition 3.** $t$ is Direct-$R$-reachable (DR) from $s$ (with respect to $S$) on $G$ iff $(s, t) \in R$ and no shortest $s$-$t$ path on $G$ passes through any $v \in S$.

**Definition 4.** $G_S = (S, E_S)$ is a subgoal graph on $G$ with respect to $S$ on $G$ iff $S$ is an R-SPC on $G$ and, $\forall u \neq v \in V, (u, v) \in E_S$ iff $v$ is direct-$R$-reachable from $u$ (with respect to $S$) on $G$.

These definitions are adapted from [Uras et al., 2013]:

**Definition 5.** An unblocked cell $s$ is a *convex corner* (of a blocked cell) iff there are two perpendicular cardinal directions $c_1$ and $c_2$ such that $s + c_1 + c_2$ is blocked and $s + c_1$ and $s + c_2$ are not blocked.

**Definition 6.** Two cells $s$ and $t$ are freespace-reachable [FR] iff at least one freespace-shortest path between them is unblocked on $G$. Two cells $s$ and $t$ are *safe-freespace-reachable* [SFR] iff all freespace-shortest paths between them are unblocked on $G$.

SGs are instantiated on grid graphs using SFR as the reachability relation and by selecting $S$ as the set of convex corners of blocked cells. Searching for shortest paths with a SG is a simple three step process sometimes referred to as Connect-Search-Refine:

1. **Connect:** The algorithm temporarily inserts $s$ and $t$ into the SG (assuming they do not already appear) and connects each of them to all DR subgoals and possibly to one another, in case that $s$ and $t$ are themselves DR.
2. **Search:** The algorithm executes a best-first search in the query SG from $s$ to $t$. Figure 3 shows an example.
3. **Refine:** Having found a subgoal path such as $\pi = \langle v_0 = s, \ldots, v_k = t \rangle$ the algorithm finds paths between each pair of adjacent subgoals $v_i$ and $v_{i+1}$ on $G$.

In [Uras and Koenig, 2017], it is shown that the Connect-Search-Refine process using SGs always finds shortest paths between any two vertices. Meanwhile, in [Uras et al., 2013], it is (implicitly) shown that the set of convex corners is an SFR-SPC on $G$. Using SFR as the reachability relation has a number of benefits:

- Refinement is trivial: For any $(s, t) \in \text{SFR}$, by definition, any freespace-shortest path is also a path on $G$.
- Edge costs are not stored (they're equal to Octile distance).
- The set of all Direct SFR (DSFR) subgoals for any cell can be identified fast using pre-computed distance-to-obstacle data (equiv. clearance values). This data also helps to speed up the Connection phase of the algorithm.

**Figure 1:** (a) Three equivalent paths connect A and B. B breaks such symmetries by taking the bold path, where diagonal moves appear first. (b) This diagonal jump point has three diagonal-first continuations: 2, 3 and 5. (c) This straight jump point also has three diagonal-first continuations: 1, 2, 4. Grey cells are pruned.

### Jump Point Search

In uniform-cost grids many *symmetric* paths can connect the same pair of vertices. Figure 1(a) shows an example.

**Definition 7.** [Harabor and Grastien, 2011] Two grid paths are symmetric iff: (i) they share the same start and target and; (ii) they have the same cost and; (iii) their constituent moves can be re-ordered to derive one path from the other.

In the presence of symmetry, otherwise efficient search algorithms, such as $A^*$, waste time, exploring many equivalent partial paths and making slow progress to the target. The Jump Point Search (JPS) family of algorithms break symmetries by maintaining the following invariant during search: when a node $n$ is added or updated on the $A^*$ open list, the path to that node is diagonal-first. This property means that the only successors generated when $n$ is expanded are those which allow the current path to continue from $n$ in a way that is taut and which guarantees that diagonal moves appear as early as possible. All other successors can be safely pruned.

**Definition 8.** A path $\pi = \langle s, \ldots, t \rangle$ is taut iff every subpath of length two $\langle n_{i-1}, n_i, n_{i+1} \rangle \in \pi$ is also a shortest path.

**Definition 9.** [Harabor and Grastien, 2011] A path $\pi$ is diagonal-first iff it contains no straight-to-diagonal turning point $\langle n_{k-1}, n_k, n_{k+1} \rangle$ which could be replaced by a diagonal-to-straight turning point $\langle n_{k-1}, n_k', n_{k+1} \rangle$ to produce a new valid path on $G$.

The diagonal-first invariant reduces the branching factor of each expanded node, often to just 0 or 1. Rather than adding such nodes to the open list, JPS immediately processes them as part of a recursive and eponymous jumping procedure. Jumping allows the search to generate and expand only a distinguished set of nodes at which diagonal-first paths can branch. These nodes are called *jump points*, of which there exist two different types:

**Definition 10.** A straight jump point is a tuple $(n, \vec{c})$ where $n$ is a cell and $\vec{c}$ is a cardinal travel direction such that, for some $\vec{d} \perp \vec{c}$: (i) $n - \vec{c}$ is unblocked; (ii) $n + \vec{c}$ is unblocked; and (iii) $(n - \vec{c}) + \vec{d}$ is blocked.

**Definition 11.** A diagonal jump point is a tuple $(n, \vec{d})$ where $n$ is a cell and $\vec{d} = \vec{c} + \vec{c}'$ is a diagonal direction such that, for some $k$: (i) $n + k \times \vec{c}$ is an unblocked path from $n$ to a cell $n'$ such that $(n', \vec{c}')$ is a straight jump point or; (ii) $n + k \times \vec{c}'$
is an unblocked path from \( n \) to a cell \( n' \) such that \((n',c_2)\) is a straight jump point; or (iii) \( n + k \times c_1 \) or \( n + k \times c_2 \) is an unblocked path from \( n \) to the target.

**Target Detection:** JPS treats the target as a special case. While scanning the grid and jumping from one node to the next, JPS detects the target and generates it as a successor.

Figures 1(b) and 1(c) show different jump points and their taut diagonal-first continuations. Figure 2 shows a complete example of pathfinding with JPS. Only diagonal-first paths are explored, and every turning point on each diagonal-first path is a jump point. Together with target detection, these features are sufficient to find a shortest path, from any start to any target, if a path exists at all.

**Lemma 1.** For every shortest path \( \pi \) on \( G \), there exists an equivalent path \( \pi' \) on \( G \) which is diagonal-first.

Some advantages of JPS compared to SG: (i) it runs entirely online; (ii) it requires no preprocessing or insertion; and (iii) it prunes successors more aggressively and often finds the target faster [Harabor and Grastien, 2014]. Some disadvantages:

- The jumping rules are not easily reversed, which means JPS is implemented only as a uni-directional search;
- JPS constantly refers to the input grid to break symmetries and detect the target. These features make JPS difficult to integrate with speedup techniques such as Contraction Hierarchies [Geisberger et al., 2008].

To overcome these limitations, we are going to develop a new and graph-theoretic perspective of JPS. In the process, we also show that JPS and SG are closely related.

**Jump Point Graphs**

To begin, we formalise the search space of JPS as a graph \( G^* \).

**Definition 12.** Let \( G = (V,E) \) be a grid graph. Its corresponding direction-extended grid graph \( G^* = (V^*, E^*) \) is defined as:

- For each vertex \( n \in V \) and each possible grid move \( \vec{v} \), there exists a vertex \((n,\vec{v}) \in V^* \).
- For each \((n_1,n_2) \in E \) and each pair of grid moves \( \vec{v}_1 \) and \( \vec{v}_2 \), there exists \((n_1,\vec{v}_1),(n_2,\vec{v}_2) \in E^* \) iff:
  1. \( n_1 + \vec{v}_1 = n_2 \)
  2. \( \langle n_1 - \vec{v}_1, n_1, n_2 \rangle \) is diagonal-first and taut.

\( G^* \) is analogous to \( G \) but each cell appears 8 times: once for each direction. Intuitively, \( G^* \) labels each vertex \( n \) of \( G \) with each possible incoming direction \( \vec{v} \), and limits the outgoing directions \( \vec{v}' \) from \((n,\vec{v}) \) to be diagonal-first and taut with \( \vec{v}' \).

**Lemma 2.** Any path \( \pi^* \) on \( G^* \) is diagonal-first and taut.

**Proof.** \( G^* \)'s edges are defined such that (1) for each vertex \((n,\vec{v}) \in V^*\), \((n,\vec{v}) \) is reachable only with move \( \vec{v} \), and (2) each move corresponding to an outgoing edge of \((n,\vec{v}) \) is diagonal-first and taut with \( \vec{v} \). Thus, for any path \( \pi^* \) on \( G^* \), any two consecutive moves are diagonal-first and taut.

**Lemma 3.** Let \( \pi = \langle n_0,...,n_k \rangle \) be a diagonal-first and taut path on \( G \). Then, there exists \( \bar{v}_0,...,\bar{v}_k \) such that \( \pi^* = \langle (n_0,\bar{v}_0),...,(n_k,\bar{v}_k) \rangle \) is a path on \( G^* \).

**Proof.** The proof follows from Definition 12 by selecting, for \( i = 1,...,k \), \( \bar{v}_i \) as the direction that satisfies \( n_{i-1} + \bar{v}_i = n_i \), and selecting \( \bar{v}_0 = \vec{v}_1 \).

Recall that, for any \( s,t \in V \), there exists a diagonal-first shortest \( s\rightarrow t \) path on \( G \) (Lemma 1) which, by Lemma 3, is preserved on \( G^* \). Therefore, we can use \( G^* \) for finding shortest \( s\rightarrow t \) paths on \( G \), by treating all \((s,\vec{v})\) as start vertices and treating all \((t,\vec{v})\) as target vertices, for all directions \( \vec{v} \).

By definition, \( G^* \) contains any (straight or diagonal) jump point on \( G \). We now show that the set of straight jump points is a freespace-reachability-SPC on \( G^* \), by extending the definitions of freespace-shortest paths and freespace-reachability (Definition 6) to \( G^* \). We use the prefix *diagonal-first* to distinguish these definitions on \( G^* \) from their counterparts on \( G \), and to better characterise their properties.

**Definition 13.** The diagonal-first freespace-shortest path from a cell \( n \) to \( n' \) is a freespace-shortest path where all diagonal moves appear before cardinal ones. A vertex \((n',\vec{v}) \in V^* \) is diagonal-first freespace reachable [DFFR] from \((n,\vec{v}) \in V^* \) iff a path from \((n,\vec{v}) \) to \((n',\vec{v}) \) on \( G^* \) corresponds to the diagonal-first freespace-shortest path from \( n \) to \( n' \). We use DFFR to denote Direct-DFFR-Reachable.

**Theorem 1.** Straight jump points form a DFFR-SPC on \( G^* \).

**Proof.** Let \( s^* = (s,\vec{v}),t^* = (t,\vec{v}) \in V^* \), such that an \( s^*\rightarrow t^* \) path exists on \( G^* \). We show that, if \((s^*,t^*) \not\in \text{DFFR}\), then a shortest \( s^*\rightarrow t^* \) path on \( G^* \) passes through a straight jump point. For contradiction, assume that \((s^*,t^*) \not\in \text{DFFR}\), and that no shortest \( s^*\rightarrow t^* \) path on \( G^* \) passes through a straight jump point. Let \( \pi^* \) be any shortest \( s^*\rightarrow t^* \) path on \( G^* \). By our assumption, \( \pi^* \) does not pass through a straight jump point. By Lemma 2, \( \pi^* \) is diagonal-first and taut. \( \pi^* \) cannot have a cardinal-to-cardinal turn because, otherwise, it is either non-taut or it passes through a jump point. \( \pi^* \) cannot have a diagonal-to-diagonal turn because, otherwise, it is either non-diagonal-first or it passes
through a jump point. Therefore \( \pi^* \) can only have diagonal-to-cardinal turns. There is only one such possible \( \pi^* \), which corresponds to the diagonal-first freespace-shortest \( s,t \) path \( \pi \). But then, the diagonal-first freespace-shortest \( s,t \) path is unblocked, contradicting that \( (s^*,t^*) \notin \text{DDFFR} \).

We may formalise the relation between SG and JPS as so:

**Theorem 2.** Subgoal reachability is a more restrictive notion than jump point reachability. Formally, \( \text{DSFR} \subseteq \text{di} \text{(DDFFR)} \), where \( \text{di}(R) \) is the relation defined as \( (s,t) \in \text{di}(R) \) iff \( \exists \vec{v}_1, \vec{v}_2, ((s,\vec{v}_1), (t,\vec{v}_2)) \in R \).

**Proof.** Consider \( (s,t) \in \text{DSFR} \). By definition, the diagonal-first freespace-shortest \( s,t \) path \( \pi \) is unblocked and does not pass through a subgoal. For some \( s^* = (s,\vec{v}_1) \) and \( t^* = (t,\vec{v}_2) \), let \( \pi^* \) be an \( s^*,t^* \) path on \( G^* \) that corresponds to \( \pi \). By Lemma 3, such \( \vec{v}_1, \vec{v}_2 \), and \( \pi^* \) exists since \( \pi \) is diagonal-first and taut (freespace-shortest). Since \( \pi \) does not pass through corner points, \( \pi^* \) does not pass through straight jump points. Therefore, \( (s,t) \in \text{di}(\text{DDFFR}) \).

Theorem 2 suggests that searching over jump points may require fewer expansions per instance than searching over an equivalent SG. Consider that JPS travels from one vertex to the next, stopping only at corner vertices where shortest paths can bend. By comparison, SG search will stop at every corner vertex along the way. Figure 3 shows an example.

Next, consider the subgoal graph \( G_j^* = (J,E_j) \) constructed on \( G^* \) using the set of straight jump points \( J \) as subgoals. From the theory presented in [Uras and Koenig, 2017] and the result of Theorem 1, \( G_j^* \) can be used to find shortest paths as long as the following conditions hold:

1. (Preprocessing) We add edges between every pair of straight jump points that are DDFFR from one another.
2. (2) We connect the start \( s \) to every straight jump point that is DDFFR from \( (s,\vec{v}) \), for any direction of \( \vec{v} \).
3. (3) We connect the target \( t \) from every straight jump point for which \( (t,\vec{v}) \) is DDFFR, for any direction of \( \vec{v} \).
4. (4) We connect the start to the target: \( s \) to \( \vec{c} \), and \( \vec{d} \), \( (s,\vec{v}) \) is DDFFR from \( (s,\vec{v}) \).

We call the resulting method the Jump Point Graph (JP). Since JP can be considered a Subgoal Graph on \( G^* \), we discuss in the following sections: how to efficiently identify its edges, how to quickly perform the Connection step and how to combine JP with other orthogonal speed-up techniques, including bi-directional search and Contraction Hierarchies.
of \( \vec{d} \) diagonal moves that can be made from \( n \) to reach a cell \( m \) where \( C[m, c_1] > 0 \) or \( C[m, c_2] > 0 \) (that is, the row or column of \( m \) contains an important cell). \( C[n, d] = 0 \) if such \( m \) does not exist. Diagonal clearances allow one to quickly traverse the diagonal by skipping the rows and columns that do not contain important cells.

The main difference between SG connect and JP forward connect is when they terminate their scans. Namely, a \( \vec{c} \) cardinal or \( \vec{d} \) diagonal-first scan of SG connect stops immediately when it finds a subgoal (as any continuation of the scan can only find subgoals that are not DSFR), whereas a \( \vec{c} \) cardinal scan of JP forward connect is a DFFR-SPC. The only differences is that, by adding more jump points in diagonal directions at every convex corner. This can be achieved by adding additional jump points in diagonal directions at every convex corner. Namely, for any convex corner \( n \) where \( n - c_1 \) and \( n - c_2 \) is unblocked but \( n - \vec{d} \) is blocked (with \( \vec{d} = c_1 + c_2 \) diagonal), we add the jump points \( (n, c_1 - c_2) \) and \( (n, c_2 - c_1) \). This variant still contains all the straight jump-points and, therefore, its set of jump points is a DFFR-SPC. The only differences is that, by adding more jump points, we allow Algorithm 1 to terminate its scans earlier. We call this variant JPD. For instance, in Figure 4, adding the diagonal jump point \( (E5, Up+Left) \) results in the Up+Left diagonal-first scan from \( (F6, Up) \) does not stop at \( E5 \) since \( E5 \) does not have a jump point \( (F5, Up+Left) \).

**Diagram Merged Jump Point Graphs**

In this section we describe a variant of JP that achieves \( O(WH) \) preprocessing time and contains \( O(WH) \) edges, similar to SG. As hinted in the previous section and in the proof of Theorem 3, this new variant should terminate its \( \vec{d} \) diagonal-first scans when the scan reaches a convex corner. This can be achieved by adding additional jump points in diagonal directions at every convex corner. Namely, for any convex corner \( n \) where \( n - c_1 \) and \( n - c_2 \) is unblocked but \( n - \vec{d} \) is blocked (with \( \vec{d} = c_1 + c_2 \) diagonal), we add the jump points \( (n, c_1 - c_2) \) and \( (n, c_2 - c_1) \). This variant still contains all the straight jump-points and, therefore, its set of jump points is a DFFR-SPC. The only differences is that, by adding more jump points, we allow Algorithm 1 to terminate its scans earlier. We call this variant JPD. For instance, in Figure 4, adding the diagonal jump point \( (E5, Up+Left) \) results in the Up+Left diagonal-first scan from \( (F6, Up) \) to terminate at \( E5 \), the first convex corner that it scans.

At first glance JPD seems to add many nodes to the jump point graph. However, each new diagonal jump point is equivalent to an existing straight jump point. In Figure 4 we can see that \( (E5, Up+Left) \) has the same successors as \( (E5, Up) \). Hence we merge these two jump points in JPD into a single jump point without changing the graph connectivity. Since each new diagonal jump point is merged with an existing straight jump point, JPD has no more jump points than JP. Notice however that JPD search may stop at corner points where JP search would not. We will see this in experiments.
A main advantage of this representation is that there is no need for explicit refinement: for every pair of adjacent vertices \( n_i, n_{i+1} \in \pi \), there always exists a diagonal-first sequence of unblocked cells in the grid, which can be generated without search.

**Avoidance Tables:** We now discuss how to speed up insertion of the start and target. Notice in Figure 6 that there are 4 convex corner points, and 8 jump points, two at each marked location. Yet only the jump points at \( a \) and \( b \) are interesting: the \( x \) jump points cannot be reached except if we connect to them during the insertion of the start or target.

In graphs with concave components, there can be a large number of these uninteresting jump points. To reduce the overhead of start and target insertion, we introduce an avoidance table for such jump points. When we insert the start, we mark in the avoidance table each such jump point that it connects to. When inserting the target, if we try to connect to a jump point in the avoidance table which is not marked, we omit the connection (since the jump point has no predecessors including the start).

**Experimental Setup**

We run experiments on a large set of standard grid-based pathfinding benchmarks [Sturtevant, 2012] and on the subset of instances from the 2014 Grid-based Path Planning Competition (GPPC). Our reference point in this comparison is CH-G, a fast implementation of Contraction Hierarchies [Geisberger et al., 2008] which appears undominated at the competition. This algorithm stores no downward edges and uses bi-directional Dijkstra search to find a path. It also benefits from stall-on-demand, a common optimisation. To refine a path CH-G uses midpointer unpacking.

Our main experiment compares the following algorithms:

- **SG**, also called Subgoal Simple in [Uras et al., 2013];
- **JP** and **JPD**, as described in the current paper;
- **CH-SG, CH-JP and CH-JPD**, all of which apply CH on top of each basic method.

We run all algorithms on a 3.6GHz Intel Core i7-7700 CPU with 32GB of RAM. Our implementations are based on C++ code from CH-SG [Uras and Koenig, 2018]. From this common base we derive all algorithms except CH-G. Similar to [Uras and Koenig, 2018], all searches use the Octile distance heuristic and a binary heap priority queue. Unlike [Uras and Koenig, 2018], SG and CH-SG store clearances in all eight directions per grid cell, as opposed to only four. JP and JPD scan E5, but while JP recurses to C3, the insertion of JPD does not.
CH-JP store clearances in both the forward and backward directions, for a total of 16 clearances per cell. Each clearance is stored using only 1 byte and clearance values longer than 255 are extracted in multiple steps.

**Results**

We begin with Table 1 which compares the different methods on the set of maps and instances from GPPC 2014 that are drawn from games. Games are one of the principal uses of grid maps and here we clearly see the impact of Theorem 2: JP has many fewer edges than SG, it expands many fewer nodes, it has a smaller branching factor and its runtime performance is faster by several factors. In combination with Contraction Hierarchies the performance gap is reduced. Here we make three observations: (i) most of the advantage that CH-JP has vs. CH-SG comes from having a faster Search and faster Refine stage. (ii) the Connect stage of both algorithms is comparable; i.e. despite JP target insertion having worst-case linear time requirements we find that the procedure is fast in practice; (iii) both CH-JP and CH-SG faster than CH-G, a method that is undominated at the competition.

In Table 2 we include additional benchmarks from Sturtevant’s well known repository and we consider the full set of maps and instances from GPPC 2014. We again observe that JP and JPD achieve shorter query times than SG. However, when combined with CH, we observe that CH-SG is faster than CH-JP and CH-JPD on each of: random, room, and maze maps with small corridor widths. We think that JP and JPD do not combine with CH as well as SG for the following reason: In JP and JPD, multiple jump points may share a cell, but are treated as different vertices. Moreover, the shortest paths between some pairs of jump points in JP or JPD might be longer than the shortest path between the cells that contain these jump points (for instance, if the start jump point has the wrong direction to lead the search to the target jump point). When applying CH to JP or JPD without prior knowledge of this fact, the CH construction algorithm tries to preserve these suboptimal paths, which can introduce redundant edges. Our CH-JP and CH-JPD implementations eliminate most of these redundant edges during contractions, by performing distance computations. Hence CH-JP improves upon JP.

**Conclusion**

In summary, we introduce JP which is uniformly better than SG, even on random maps where there end up being many more jump points than subgoals. We allow the use of contraction hierarchies for jump point search for the first time, improving the state-of-the-art in path planning for the important category of game maps.

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**References**


Table 1: Comparison on the subset of GPPC 2014 maps and instances which are drawn from computer games. There are 27 maps from DAO, 67 maps from DA2 and 11 from StarCraft. We give average graph size for each algorithm (A* runs on input grid maps) and we report performance metrics for nodes (average expansions, average successors per expansion) and runtime (total as well as for each of Connect-Search-Refine). Columns Prep and Memory indicate overheads.

Table 2: Number of edges relative to the grid graph $G$ and the speed up over $A^*$ on $G$. All maps from MovingAI benchmarks are included, except for the last 20 of the 30 street-1024 maps, due to high CH-SG preprocessing times.