Bidirectional Heuristic Search: Expanding Nodes by a Lower Bound (Extended Abstract)*

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Abstract

Recent work on bidirectional search defined a lower bound on costs of paths between pairs of nodes, and introduced a new algorithm, NBS, which is based on this bound. Building on these results, we introduce DVCBS, a new algorithm that aims to further reduce the number of expansions. Generalizing beyond specific algorithms, we then propose a method for enhancing heuristics by propagating such lower bounds (lb-propagation) between frontiers. This lb-propagation can be used in existing algorithms, often improving their performance, as well as making them "well behaved".

1 Introduction and Background

Bidirectional heuristic search (Bi-HS) algorithms interleave two separate searches: forward from start, and backward from goal. Recently, Eckerle et al. [2017] defined conditions on pairs of nodes that must be expanded by Bi-HS algorithms to guarantee solution optimality. Chen et al. [2017] reformulated these conditions as a lower bound (lb) on costs of paths between nodes, and used this lb to introduce NBS, a non-parametric Bi-HS algorithm with an upper bound on the node expansions required to verify solution optimality.

In this paper* we present DVCBS, a new algorithm that uses the lb information differently than NBS and empirically compare them, showing that DVCBS outperforms NBS on average. In addition, we generalize beyond specific algorithms and show a connection between utilizing the lb information and two desirable properties for Bi-HS algorithms: the well-behaved property, where using a better heuristic never harms performance; and the reasonable property, that guarantees an algorithm never expands nodes with an lb greater than the known global lower bound (LB) on an optimal solution. Then, we present lb-propagation, a method for sharing the best lb between the two search frontiers, improving the h-}

*This paper summarizes the paper: “Improving Bidirectional Heuristic Search by Bound Propagation” ([Shperberg et al., 2019b]) which won the best-paper award at SoCS-2019, with some additions from the paper: “Enriching non-parametric Bidirectional Search Algorithms” ([Shperberg et al., 2019a]).

and f-values in each frontier. Finally, we study a number of algorithms and show that adding lb-propagation makes some (but not all) algorithms well-behaved and reasonable, and empirically reduces the number expanded nodes in many cases.

1.1 Definitions and Notations

Given a distance metric \(d(x, y)\) between nodes in an (implicitly defined) graph \(G = \{V, E\}\), the aim of a shortest-path problem is to find a least-cost path between two given vertices \(start\) and \(goal\) in \(G\), with \(C^* = d(start, goal)\). Most Bi-HS algorithms maintain two open lists: \(Open_F\) for the forward search and \(Open_B\) for the backward search.

Given a direction \(D\) (either forward or backward) We use \(f_D, g_D\) and \(h_D\) to indicate \(f\)-, \(g\)-, and \(h\)-values in direction \(D\). W.l.o.g., the known minimal edge cost in \(G\) is denoted by \(c\), with \(c = 0\) if a greater value is not known.

The heuristic \(h_D\) in direction \(D\) is admissible iff \(h_D(u) \leq d(u, g)\) for every node \(u \in G\) and is consistent iff \(h_D(u) \leq d(u, u') + h_D(u')\) for all \(u, u' \in G\). Let \(I_{AD}\) be the set of problems with admissible heuristics, and \(I_{CON}\) \(\subseteq I_{AD}\) be the set of problems with consistent heuristics. A search algorithm is admissible on a set of problems \(I\) if it is guaranteed to find an optimal solution on every problem \(i \in I\). Finally, a heuristic \(h_1\) is said to dominate another heuristic \(h_2\) if for every node \(n \in G, h_1(n) \geq h_2(n)\) [Russell and Norvig, 2016].

1.2 Guaranteeing Solution Optimality

Unidirectional search algorithms must expand all nodes \(n\) with \(f(n) < C^*\) in order to guarantee solution optimality [Dechter and Pearl, 1985]. Eckerle et al. [2017] generalized this to Bi-HS by examining pairs of nodes \(\langle u, v \rangle\) with \(u \in Open_F\) and \(v \in Open_B\).

Definition 1. For each pair of nodes \(\langle u, v \rangle\) let \(lb(u, v) = \max\{f_F(u), f_B(v)\} + g_F(u) + g_B(v) + \epsilon\}

In Bi-HS, a pair of nodes \(\langle u, v \rangle\) is called a must-expand pair (MEP) if \(lb(u, v) < C^*\). For each MEP only one of \(u\) or \(v\) is expanded.
must be expanded in order to ensure that there is no path from start to goal passing through u and v of cost < C*. In the special case of unidirectional search, algorithms expand all the nodes with \( f_F < C^* \), which is equivalent to expanding the forward node of every MEP. Bi- HS algorithms may expand nodes from either side, potentially covering all the MEPs with fewer expansions.

In order to bound the minimal solution cost that can pass through each (single) node \( u \) in the open lists, we use the bound \( lb(u,v) \), apply it to every node \( v \) in the opposite frontier and take the minimum of these values. Formally, for every \( u \) in \( Open_D \) let \( lb(u,v) = \min_{v \in open_D} \{lb(u,v)\} \) (\( D \) is opposite to \( D \)). Then \( lb(u) \) is a lower bound on the cost of any solution that passes through \( u \). Finally, we define the global lower bound \( LB \) to be the minimal \( lb(u) \) among all nodes.

\( lb \) was reformulated by Chen et al. [2017] as a bipartite graph (called a Must-Expand Graph or \( G_{MX} \)) in which for each node \( u \in G \) there is a left vertex \( u_F \) and a right vertex \( u_B \); a \( G_{MX} \) has an edge between a vertex \( u_F \) and a vertex \( u_B \) iff \( (u, v) \) is an MEP. Under this representation, the task of covering all the MEPs is equivalent to finding a vertex cover (VC) of the \( G_{MX} \), and the minimum vertex cover (MVC) is the minimum number of expansions required to prove solution optimality. Chen et al. [2017] then used the \( G_{MX} \) representation to develop NBS, a Bi- HS algorithm that chooses an edge form the \( G_{MX} \) in every iteration, and expands both nodes. NBS terminates once a solution with cost \( \leq LB \) is found. By only expanding edges of the \( G_{MX} \), NBS is bounded by \( 2 \times \lceil \text{MVC} \rceil \) and thus expands at most twice the number of nodes required to verify solution optimality.

2 Bidirectional Search using Dynamic VC

Based on the above lower bounds, we introduce the Dynamic Vertex Cover Bidirectional Search (DVCBS) algorithm. Like NBS, DVCBS maintains \( LB \) and terminates when a solution with cost \( \leq LB \) is found. However, DVCBS differs conceptually from NBS: while NBS always expands both nodes of a chosen edge (MEP), DVCBS works by maintaining a dynamic version of a \( G_{MX} \) (a \( DG_{MX} \)), greedily expanding a minimum vertex cover of the \( DG_{MX} \) at each step.

The structure of a \( DG_{MX} \) resembles that of a \( G_{MX} \), with two main differences: (1) The full \( G_{MX} \) is unknown during the search. As a result, a \( DG_{MX} \) constructs left and right vertices using only nodes in \( Open_F \) and \( Open_B \) respectively. (2) The value of \( C^* \) is not known during the search, thus edges of a \( DG_{MX} \) are defined on pairs \((u, v)\) such that \( lb(u,v) < LB \). Since \( LB \leq C^* \), all such pairs are MEPs in the relevant full \( G_{MX} \). Note that nodes with the same \( g \)-value in the \( G_{MX} \) (and \( DG_{MX} \)) can be merged into a single weighted vertex, or cluster, where the task is to find a minimum weighted VC.

2.1 Choosing Nodes for Expansion

There are many ways to choose nodes for expansion given a \( DG_{MX} \) and an MVC. Every expansion deletes vertices of, and may add new vertices to the \( DG_{MX} \), invalidating the given MVC. However, computing an MVC every time the \( DG_{MX} \) changes incurs some overhead. Thus, an efficient expansion policy should balance between expanding more nodes and maintaining relevant \( DG_{MX} \) and MVC. We experimented with various expansion policies, and found that a good balance is to expand a single cluster before re-computing the \( DG_{MX} \) and MVC. This results in a manageable number of MVC computations, while working with reasonably up-to-date information. Moreover, since all vertices in a cluster share \( g \)-values, \( LB \) may only be increased after an entire cluster is expanded. We only report experimental results for this variant.

DVCBS contains several other decision points. First, there can be many possible MVCs for a given \( DG_{MX} \). Additionally, as mentioned above, one cluster from an MVC should be chosen and expanded. Finally, the order of node expansions within a cluster may affect the number of expansions before reaching a solution when \( LB = C^* \). We experimented with many variants but found the best to be as follows: select the cluster with the least amount of nodes among the clusters with minimal \( g_F \)- and \( g_B \)-values, among all MVCs. Tie breaking within a cluster orders nodes according to the order of their discovery. The results reported in Section 2.2 use this variant.

The core of DVCBS includes the following steps: (1) initialize the \( DG_{MX} \), (2) find an MVC, (3) expand a cluster from the MVC and (4) update the \( DG_{MX} \). Steps 2-4 repeat until either an optimal solution is found or no solution can exist. While DVCBS outperforms NBS on average (see experiments below), DVCBS is not bounded in its worst case.

2.2 Evaluating DVCBS

In order to empirically evaluate DVCBS, we ran experiments on the following domains: (1) 50 Pancake Puzzle (with 14 pancakes) instances with the GAP heuristic [Helmert, 2010]. To get a range of heuristic strengths, we also used the GAP-\( n \) heuristics (\( n = 1 \ldots 9 \)) where the \( n \) smallest pancakes are deleted from the heuristic computation; (2) 50 12-disk, 4-peg Towers of Hanoi (TOH4) instances with additive PDBs [Felner et al., 2004]. (3) Grid-based pathfinding: maps from Dragon Age Origins (DAO) [Sturtevant, 2012], each with different start and goal points. (4) The standard 100 instances of the 15 Puzzle problem [Korf, 1985] using Manhattan Distance. Our results are reported in Table 1 in which “VC: \( G_{MX} \)” denotes the nodes expansions before finding a VC of the \( G_{MX} \), and “Total” denotes that overall total expansions.

<table>
<thead>
<tr>
<th>Domain</th>
<th>Heuristic</th>
<th>Algorithm</th>
<th>VC: ( G_{MX} )</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pancake</td>
<td>GAP</td>
<td>NBS</td>
<td>47</td>
<td>147</td>
</tr>
<tr>
<td></td>
<td>GAP-1</td>
<td>NBS</td>
<td>5,870</td>
<td>5,915</td>
</tr>
<tr>
<td></td>
<td>GAP-2</td>
<td>NBS</td>
<td>137,295</td>
<td>137,719</td>
</tr>
<tr>
<td>Puzzle</td>
<td>MD</td>
<td>NBS</td>
<td>12,709,517</td>
<td>12,748,107</td>
</tr>
<tr>
<td>DAO</td>
<td>Octile</td>
<td>NBS</td>
<td>6,561</td>
<td>6,677</td>
</tr>
<tr>
<td>TOH4</td>
<td>10+2</td>
<td>NBS</td>
<td>232,509</td>
<td>232,509</td>
</tr>
<tr>
<td></td>
<td>6+6</td>
<td>NBS</td>
<td>663,356</td>
<td>664,406</td>
</tr>
</tbody>
</table>

Table 1: Average node expansions across domains (using \( \epsilon = 1 \))
As NBS has a 2\times bound guarantee, any algorithm must expand at least half of those expanded by NBS, limiting possible improvements. Nevertheless, we found DVCBS required less expansions to find a VC of the $G_{Mx}$ and a solution. Finally, the expansion rates of both algorithms were similar, with very low variance. Therefore, the number of node expansions reported in Table 1 reflects the run-time accurately.

Both DVCBS and NBS are algorithms specifically designed to utilize $lb(u,v)$. We now introduce interesting theoretical properties that may be gained by using the $lb$ information. In addition, we propose a way to incorporate this information into existing algorithms that do not include it by design.

## 3 Well-Behavedness and Reasonableness

If $h_1$ and $h_2$ are consistent heuristics and $h_1$ dominates $h_2$, then $h^*$ using $h_1$ will expand a subset of the nodes expanded when using $h_2$, up to tie-breaking in the last $f$-layer [Holte, 2010]. Holte et al. [2017] defined the meet-in-the-middle (MM) Bi-HS algorithm and presented an anomaly in which the above property is violated. Specifically, they presented an example in which MM (an MM variant with a global zero-heuristic, $h_0$) expands a subset of nodes that are expanded by MM with a stronger heuristic. Barley et al. [2018] also refer to this anomaly, calling algorithms well-behaved if using a stronger heuristic does not cause any additional node expansions, and ill-behaved otherwise. Well-behavedness has not been formally defined in a general manner. Therefore, we introduce a general definition of the well-behavedness property below and show that the anomaly stems from a combination of (1) different tie-breaking, and (2) ignoring the theoretical lower-bound conditions in the expansion process.

Many heuristic search algorithms only partially specify which node to expand at each step. For example, $A^*$ may choose any node in OPEN with a minimal $f$-value. Thus, these algorithms specify a set of nodes to be expanded (the allowable-set) from which the next node must be expanded. A tie-breaking scheme is used to select a node from the allowable-set. Such schemes are usually implementation-specific, rather than part of the algorithm definition.

Let $A_h(I,t)$ be the sequence of nodes expanded by running algorithm $A$ using heuristic $h$ on problem instance $I$ with a tie-breaking function $t$, and let $S(A_h(I,t))$ be a (unordered) set of nodes induced by the expansion performed by $A_h(I,t)$.

**Definition 2.** Let $h_1, h_2$ be admissible, consistent heuristics, such that $h_1$ dominates $h_2$. Algorithm $A$ is said to be well-behaved if for every tie-breaking policy $t$ and problem instance $I$, there exists a tie-breaking policy $t'$ such that $S(A_{h_1}(I,t')) \subseteq S(A_{h_2}(I,t))$.

This general definition applies to any Bi-HS algorithm. To date, only $A^*$ and GBFS were shown to be well-behaved, and MM has been shown to be ill-behaved. Based on $lb$, we define conditions that determine whether algorithms are well-behaved, covering many more algorithms.

**Theorem 1.** An admissible Bi-HS algorithm $A$ is well-behaved if the following three sufficient (but not necessary) conditions hold: (C1) $A$ chooses a node $v$ for expansion only if $lb(u) = LB$; (C2) $A$ terminates when a solution with cost $C \leq LB$ is found; and (C3) the allowable-set of $A$ contains every node $u$ with $lb(u) = LB$.

While being well-behaved is an interesting property, some well-behaved algorithms that do not satisfy C1-C3, do not behave sensibly. For example, an algorithm that completely ignores heuristic values and expands nodes by their $g$-value is clearly well-behaved because a stronger heuristic would not affect the algorithm’s behavior. However, such an algorithm might expand nodes $n$ with $f(n) > C^*$ whose $g(n) \leq C^*$. Gilon et al. [2016] denoted algorithms as reasonable if they prune any node $n$ with $f(n) > C$, where $C$ an upper bound on the cost. We generalize this notion as follows:

**Definition 3.** A Bi-HS algorithm is reasonable if for every tie-breaking policy it does not expand a node $v$ if either $lb(v) > C^*$, or if $lb(v) = C^*$ and a solution of cost $C^*$ was found.

**Theorem 2.** Any admissible Algorithm $A$ that satisfies C1 and C2 is reasonable.

To summarize, an algorithm that satisfies C1 and C2 is reasonable, and one that also satisfies C3 is well-behaved.

### 4 lb-propagation and its Effect on Algorithms

$lb$-propagation is a method for enhancing heuristics by utilizing $lb$-values. Let $h_{lb}(n) = lb(n) - g_D(n)$ denote the new heuristic for nodes in direction $D$. Maintaining and using $h_{lb}$ (by propagating $lb$ information between frontiers) instead of $h$ in an algorithm is called $lb$ propagation. Consider the following observations: (1) $h_{lb}$ is a dynamic heuristic that considers information generated by the search in direction $D$. Therefore, its value for a node may change as the search proceeds. (2) As $lb(n) \geq f_D(n)$ holds, $h_{lb}(n) \geq h_D(n)$ for every node in both directions. (3) $h_{lb}$ maintains the consistency and admissibility properties of $h$.

Despite the fact that $h_{lb}$ dominates $h(n)$, $lb$-propagation depends on the ability to efficiently compute the $lb$ of nodes in OPEN. In some algorithms, the $lb$-propagation can be applied to a subset of OPEN, possibly enabling efficient $lb$ computation (as in NBS). Another possibility is to use $g$-h buckets [Burns et al., 2012]; this solution is very efficient when the number of possible $g$-values is relatively small.

$h_{lb}$ changes the $f$-values of nodes to be their $lb$-value, thus, any algorithm that expand nodes and terminates based on $f$-values, and applies $lb$-propagation will now satisfy condition C1 and C2 and become reasonable. However, in order to be provably well-behaved, condition C3 is also needed.

Table 2 shows the effect of $lb$-propagation on several algorithms: BHPA [Pohl, 1971], BS* [Kwa, 1989], fMM [Shaham et al., 2017], NBS, DVCBS and GBFS [Barley et al., 2018].

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Without lb-p</th>
<th>With lb-p</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R</td>
<td>WB</td>
</tr>
<tr>
<td>BHPA</td>
<td>×</td>
<td>✓</td>
</tr>
<tr>
<td>BS*</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>fMM</td>
<td>×</td>
<td>✓</td>
</tr>
<tr>
<td>GBFSH</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>NBS, DVCBS</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Table 2: Algorithm properties summary. R columns denote reasonableness, WB columns denote well-behavedness.
5 Empirical Evaluation of \(lb\)-propagation

The evaluation of the \(lb\)-propagation was performed using the same settings reported in section 2.2 with the following exceptions: (1) 10 pancaked were used instead of 14 (2) 10 disk were used in TOH4 instead of 12. (3) the 15 Puzzle problem domain was excluded. These changes were made since many of the algorithms evaluated in this section could not solve the original (more complex) problems in reasonable time.

Figure 1 shows average node expansions in the 10-pancake domain across all GAP heuristics. Figure 1 (left) compares \(MM\) and \(MM_{lb}\), clearly showing that \(h_{lb}\) reduces the number of expansions in each of the GAP heuristics up until the heuristic effectively becomes \(h_0\). The presence of the anomaly is demonstrated by the hump-in-the-middle [Barley et al., 2018] in heuristics GAP-2 through GAP-6. By contrast, the hump-in-the-middle of \(MM_{lb}\) is not present in when considering average expansions. Figure 1 (right) compares a variant of BHPA, denoted by BHPA-Min, with the \(lb\)-enhanced BHPA-Min. This variant selects the frontier that includes the node with the minimal \(f\)-value. Here too, the \(lb\)-propagation improves the search by reducing the number of nodes expanded. Even though BHPA-Min is well-behaved, the \(lb\)-propagation still improves the algorithm by making it reasonable.

Table 3 depicts the average number of nodes expanded across domains in fewer expansions. This is also the case for GAP-4 through GAP-9, which do not appear in the table. Another interesting observation is that the hump-in-the-middle is less pronounced in all of the \(lb\)-enhanced algorithms we tested. We also experimented using \(\epsilon = 0\), and similar trends were exhibited.

6 Summary and Conclusions

We have examined the lower bounds on paths costs between pairs of nodes (\(lb\)), and presented a dynamic-vertex-cover based Bi-HS algorithm, DVCBS, that uses \(lb\) by design. Moreover, we have empirically showed that DVCBS outperforms NBS on average, despite not having any upper bound guarantees. We analyzed the advantages of using the \(lb\) information by examining the anomaly present in some Bi-HS algorithms, where using a better heuristic may lead to more node expansions. Aiming to improve some of the anomalous algorithms, we defined the “well-behavedness” and “reasonableness” properties, and established sufficient conditions (C1, C2, C3) for them based on \(lb\). Finally, we devised the \(lb\)-propagation scheme for utilizing the \(lb\) information in existing algorithms lacking this feature, that can be added to many Bi-HS algorithms, in some cases granting them these desirable properties. Empirical results show that modified algorithms exhibit better behavior, mitigating or eliminating the undesirable “hump-in-the-middle” effect.

Acknowledgements

Partially supported by ISF grant #844/17, by BSF grant #2017692, by NSF grant #1815660, by the Frankel center for CS at BGU, by CIFAR and NSERC.
References


