Iterative-deepening Bidirectional Heuristic Search with Restricted Memory

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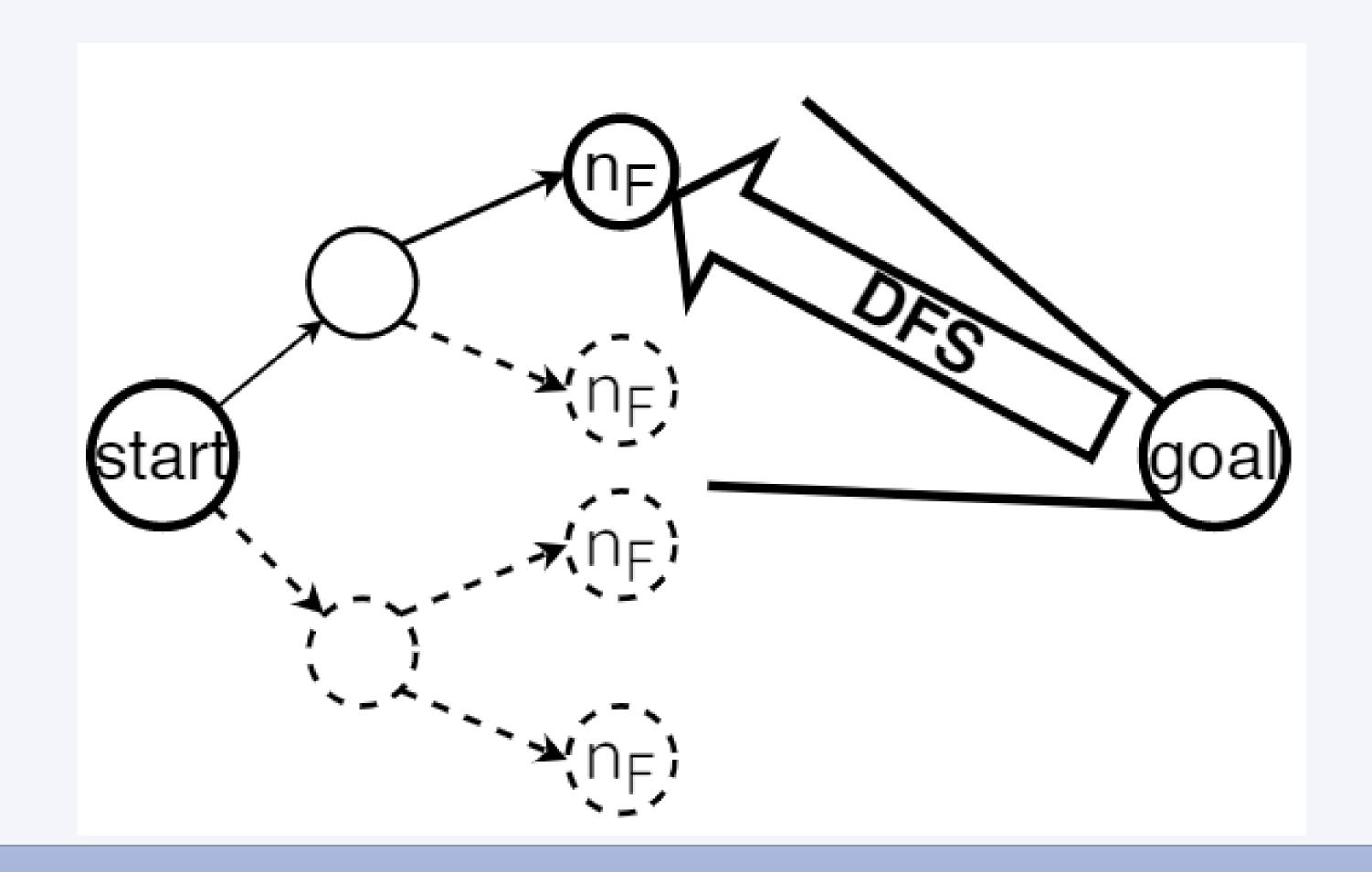
Abstract: We introduce a new bidirectional memory-bounded algorithm, called IDBiHS, that can set the meeting point between the frontiers. The basic variant of IDBiHS uses memory linear in the search depth. In addition, we introduce two other variants of IDBiHS that use fixed amount of memory. Finally, we show that in many cases our new algorithms outperform pervious ones in terms of both node expansions and time.

Memory-based classification of algorithms

- Unrestricted memory (UM): using memory proportional to the size of the explored search tree that they explored (e.g. A*).
- Restricted Memory (RM)
 - Linear memory (LM): storing a single branch of the search tree (a path), memory linear in search depth.
 - Fixed memory (FM): using fixed amount of memory M (as well as a single path).

<u>Iterative-deepening Bidirectional Heuristic Search (IDBiHS)</u>

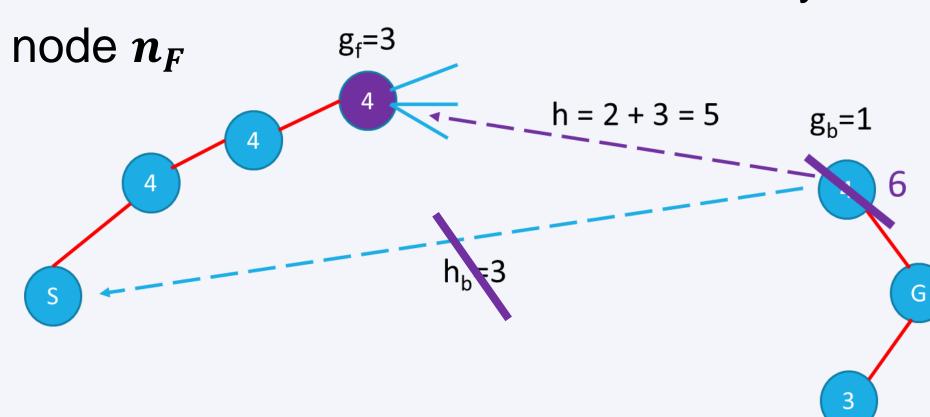
- Bidirectional search algorithm that uses linear memory
- Sets a meeting point using a split function
- Maintains a bound on the solution cost (fT)
- Split function chooses a forward g-value bound (gT_F) based on fT.
- Search nodes from *start* in a forward DFS (F_DFS) whose f-value doesn't exceed fT, and whose g-value doesn't exceed gT_F
- Once a node n_F with $f_F(n_F) \le fT$ and $g_F(n_F) > gT_F$ is found, suspend F_DFS and try to match n_F by running a backward DFS (B_DFS)
- When trying to match a node n_F , B_DFS uses the f-bound fT and a backward g-value bound defined as: $gT_B = fT g_F(n_F) \epsilon$
- If all forward nodes were search up to the threshold and a match (solution) was not found, increment fT and update gT_F using the split function.
- On each iteration there is one F_DFS run and many B_DFS runs



Reducing the Number of Node Expansions

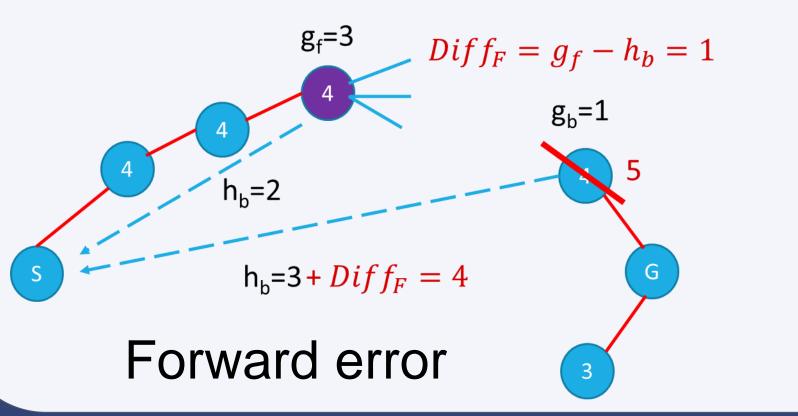
Front-to-front Heuristic

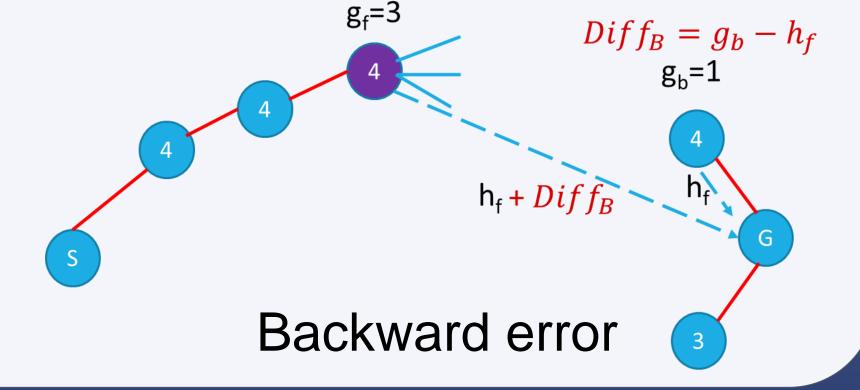
• If a front-to-front (F2F) heuristic is available, it can be used by B_DFS when trying to match a node n_F $g_f=3$



Consistent Heuristic

■ For consistent heuristics, the heuristic error along a path can be added to the heuristic of the other direction [Kaindl and Kainz, 1997]

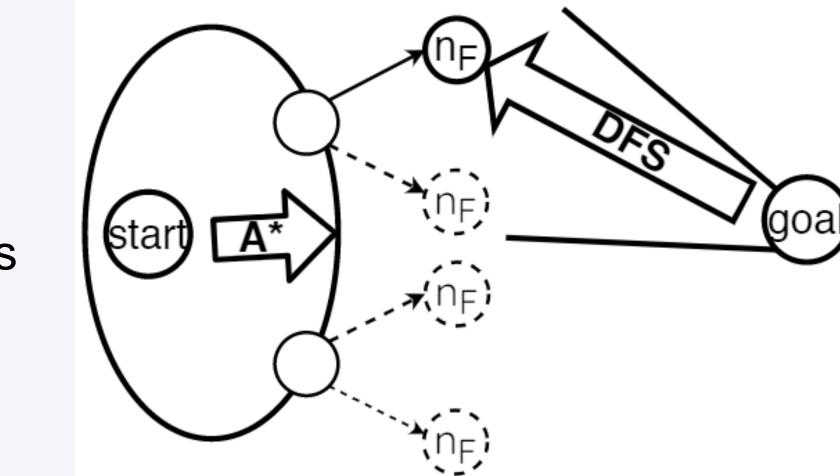




Fixed-memory Variants of IDBiHS

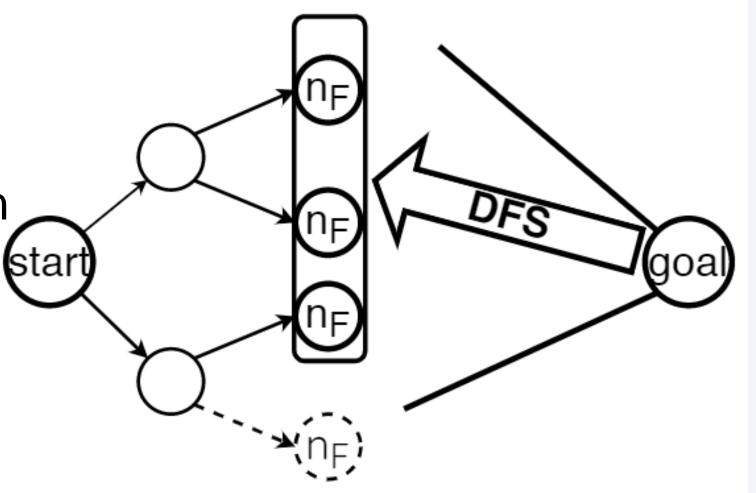
A*+IDBiHS

- Inspired by A*+IDA*
- Run A* with available memory,
 then start F_DFS from open nodes



IDBiHS-Trans

Instead of matching very n_F node individually, store them in a transposition table, then match all nodes in the transposition table at once



Empirical Evaluation

LM algorithms

Domain		Expanded							Best IDA* SFBDS IDBiHS IDBiHS					
	ı H	Best	IDA*	SFBDS	IDBiHS	IDBiHS	Best UM	IDA*	SFBDS	IDBiHS 1	DBiHS			
		UM	IDA	JIL(1)	0.5	BW		IDA	JIL(1)	0.5	BW			
P[12]	G	34(57%)	95(76%)	169(79%)	85(76%)	83(77%)	0.00	0.00	0.00	0.00				
	G-1	1,256(14%)	9,665 (72%)	8,622(74%)	3,417(70%)	2,857(72%)	0.00	0.01	0.01	0.00	0.00			
	G-2	13,089(10%)	383,488(68%)	205,469(71%)	75,205(70%)	72,939 (72%)	0.04	0.25	0.15	0.06	0.05			
	G-3	38,545 (6%)	8,601,396(66%)	4,161,889(69%)	1,540,325(71%)	1,390,806(69%)	0.13	5.44	2.90	1.14	1.03			
P[45]	G	45,822(50%)	140,574(79%)	184,809(74%)	128,912(78%)	127,743(78%)	2.32	0.94	1.25	0.85	0.84			
STP	MD	8,143,628 (2%)	242,460,834(50%)	139,225,772(46%)	174,414,968(40%)	137,331,587 (48%)	24.76	47.85	35.90	36.44	29.29			
Grid	Octile	383(70%)	47.060(75%)	131.488(78%)	210.353(78%)	122.304(79%)	0.00	0.00	0.01	0.01	0.01			

 IDBiHS is better on average in exponential domains and worse in polynomial domains (see paper for analysis)

FM algorithms

	Н	Mem	Expanded							Time(sec)				
Domain			Max- BAI	BIDA*	A*+ IDA*	A*+ IDBiHS	IDBiHS- Trans	Max- BAI	15.111.0.0 ÷	A*+ IDA*	A*+ IDBiHS	IDBiHS- Trans		
	G	50%	84(74%)	69(68%)	40(65%)	36(73%)	125(90%)	0.00	0.00	0.00	0.00	0.00		
		10%	84(78%)	75 (78%)	56(75%)	48(77%)	65(82%)	0.00	0.00	0.00	0.00	0.00		
		1%	93(76%)	96(75%)	62(78%)	54(75%)	59(78%)	0.00	0.00	0.00	0.00	0.00		
-	G-1	50%	858(47%)	2,742(43%)	932(44%)	1,129(64%)	1,630(68%)	0.00	0.00	0.00	0.00	0.00		
		10%	2,987(80%)	950 (72%)	3,435(75%)	1,021(69%)	998(64%)	0.00	0.00	0.00	0.00	0.00		
D[12]		1%	5,525(80%)	3,854(81%)	4,607 (77%)	1,345(70%)	1,203(67%)	0.00	0.00	0.00	0.00	0.00		
P[12] -	G-2	50%	20,662(62%)	16,654(50%)	96,891 (55%)	18,041 (61%)	8,243(74%)	0.03	0.12	0.09	0.06	0.05		
		10%	45,113(83%)	16,352(66%)	135,907(80%)	21,509(65%)	6,670(67%)	0.04	0.10	0.09	0.03	0.05		
		1%	113,607(79%)	27,665 (74%)	207,447 (82%)	31,866(70%)	11,924(74%)	0.09	0.08	0.25	0.03	0.06		
	G-3	50%	223,490(78%)	130,167(60%)	2,259,163(80%)	289,218(72%)	35,915(67%)	0.26	1.96	1.58	0.43	0.70		
		10%	578,231 (79%)	212,442(68%)	3,293,269(75%)	381,136(71%)	41,020(68%)	0.51	2.01	2.13	0.36	0.81		
		1%	1,631,356(75%)	318,838(68%)	4,910,121(74%)	622,505 (68%)	104,516(72%)	1.35	1.71	3.10	0.50	0.91		
	G	50%	145,410(74%)	97,663 (63%)	108,176(65%)	87,563(72%)	634,304(93%)	1.99	1.74	2.56	1.61	4.92		
P[45]		10%	134,226(78%)	128,601 (75%)	144,863 (67%)	120,340(73%)	412,355(81%)	1.10	1.01	1.32	0.87	2.97		
		1%	161,791 (79%)	162,385 (77%)	170,279(65%)	143,120(75%)	128,204(77%)	0.95	1.00	1.54	0.84	1.66		
	MD	50%	7,998,667(46%)	7,654,126(40%)	38,347,881 (65%)	15,489,868 (42%)	4,738,575 (50%)	20.83	29.16	27.94	24.02	11.69		
STP		10%	13,804,939(64%)	5,183,115(51%)	71,470,823 (74%)	24,322,900(41%)	4,447,875(47%)	9.50	13.17	17.04	12.22	8.79		
		1%	55,391,222(66%)	6,026,913 (56%)	118,002,945 (68%)	46,075,139(39%)	3,941,356(35%)	24.83	13.18 2	23.41	13.59	9.08		
	Octile	50%	8,362(75%)	14,911 (78%)	16,503 (72%)	19,880(76%)	12,833(78%)	0.00	0.00	0.00	0.00	0.00		
Grid		10%	31,439(76%)	36,417(77%)	42,914(74%)	55,964(75%)	14,388(78%)	0.00	0.00	0.00	0.00	0.00		
		1%	45,826(75%)	46,632(79%)	46,518(74%)	106,818(77%)	40,545(76%)	0.00	0.00	0.00	0.01	0.00		

new algorithms are very competitive and often outperform existing methods.