

PAPA*: Path-Aware Parallel A*

AAAI 2015 Submission X

Abstract

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Fancy Stuff

Hello world.

Algorithm 1 $bound(s)$

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 $g_{front} := \infty$ 
 $s' := \text{first node in } OPEN \cup BE$ 
 $g_{back} := g(s) + f(s') - f(s) + (2\epsilon - w - 1)c_l$ 
while  $g_{back} < g(s) \leq g_{front}$  do
     $g_{front} := \min(g_{front}, g_p(s') + \epsilon h(s', s))$ 
     $s' := \text{node following } s' \text{ in } OPEN \cup BE$ 
     $g_{back} := g(s) + f(s') - f(s) + (2\epsilon - w - 1)c_l$ 
end while
return  $\min(g_{front}, g_{back})$ 

```

Throughout this paper, we assume all edge costs are bounded below by c_l , that $\epsilon \geq 1$ and $0 \leq w \leq \epsilon$.

Definition 1 (TODO: don't need these definitions). *We say a state s is independent of s' if $g(s) \leq g_p(s') + \epsilon h(s', s)$. We say $s \in OPEN$ is safe to expand if s is independent of all $s' \in OPEN \cup BE$.*

Lemma 1. *At all times, for all states s, s' :*

$$g(s) + f(s') - f(s) + (2\epsilon - w - 1)c_l \leq g_p(s') + \epsilon h(s', s).$$

Proof.

$$\begin{aligned}
 & g(s) + f(s') - f(s) + (2\epsilon - w - 1)c_l \\
 = & g(s') + w(h(s') - h(s)) + (2\epsilon - w - 1)c_l \\
 \leq & g(s') + wh(s', s) + (2\epsilon - w - 1)c_l \\
 \leq & g(s') + \epsilon h(s', s) + (w - \epsilon)c_l + (2\epsilon - w - 1)c_l \\
 = & g(s') + \epsilon h(s', s) + (\epsilon - 1)c_l \\
 \leq & g_p(s') + \epsilon h(s', s)
 \end{aligned}$$

□

Algorithm 2 PAPA*

```

LOCK
while  $g(s_{goal}) > bound(s_{goal})$  do
    remove an  $s$  from  $OPEN$  that has the smallest  $f(s)$ 
    among all states in  $OPEN$  with  $g(s) \leq bound(s)$  and
    let  $g_{bound} := bound(s)$ 
    if such an  $s$  does not exist then
        UNLOCK
        wait until  $OPEN$  or  $BE$  change
        LOCK
        continue
    end if
    insert  $s$  into  $BE$ 
    insert  $s$  into  $CLOSED$ 
    UNLOCK
     $S := getSuccessors(s)$ 
    LOCK
    for all  $s' \in S$  do
        if  $s'$  has not been generated yet then
             $f(s') := g(s') := g_p(s') := \infty$ 
        end if
        if  $s' \notin CLOSED$  then
             $g_p(s') = \min(g_p(s), g_{bound} + \epsilon c(s, s'))$ 
            if  $g(s') > g(s) + c(s, s')$  then
                 $g(s') = g(s) + c(s, s')$ 
                 $f(s') = g(s') + wh(s')$ 
                 $bp(s') = s$ 
                insert/update  $s'$  in(to)  $OPEN$  with key  $f(s)$ 
            end if
        end if
    end for
    remove  $s$  from  $BE$ 
end while

```

Lemma 2. For all states s , $\text{bound}(s) \leq \epsilon g^*(s)$. Hence, upon expanding s , $g(s) \leq \epsilon g^*(s)$.

Proof. We proceed inductively by the order in which states are expanded. By construction, $\text{bound}(s)$ is bounded above by $g_p(s') + \epsilon h(s', s)$ for states s' which are checked in the loop. As for the remaining states $s' \in \text{OPEN} \cup \text{BE}$, the algorithm ensures that $\text{bound}(s) \leq g(s) + f(s') - f(s) + (2\epsilon - w - 1)c_l$ for these by using a minimum representative. By Lemma 1, it follows that

$$\text{bound}(s) \leq \min_{s' \in \text{OPEN} \cup \text{BE}} g_p(s') + \epsilon h(s', s).$$

We complete the proof by showing that the latter expression is bounded above by $\epsilon g^*(s)$. Fix any optimal path to s , and let s' be the first node on it which is in $\text{OPEN} \cup \text{BE}$. Let s_p be the predecessor of s' on this path. By the induction hypothesis, $g(s_p) \leq \epsilon g^*(s_p)$. Therefore,

$$\begin{aligned} \epsilon g^*(s) &= \epsilon (g^*(s_p) + c(s_p, s') + c^*(s', s)) \\ &\geq g(s_p) + \epsilon c(s_p, s') + \epsilon h(s', s) \\ &\geq g_p(s') + \epsilon h(s', s) \end{aligned}$$

□

TODO: clear up initial case where $s = s' = s_{\text{start}}$.

Algorithm 3 $\text{meanbound}(s)$ with $w \leq 1$

$s' :=$ first node in $\text{OPEN} \cup \text{BE}$

return $g(s) + f(s') - f(s) + (1 - w)c_l + 2(\epsilon - 1)c_m$

When c_l is very small but we have a good estimate for the mean edge cost, we can maximize parallelism by using $\text{meanbound}(s)$ in place of $\text{bound}(s)$. This variant of PAPA* is inspired by (Klein and Subramanian 1997).

Lemma 3. For all states s , $\text{bound}(s) \leq g^*(s) + (\epsilon - 1)c_m k(s)$ where $k(s)$ is the least number of edges used in a minimum-cost path to s . In particular, if c_m is not more than the mean cost of the edges along the minimum-cost path, then upon expansion, $g(s) \leq \epsilon g^*(s)$.

Proof. We proceed inductively by the order in which states are expanded. Fix any optimal path to s , and let s' be the first node on it which is in $\text{OPEN} \cup \text{BE}$. Let s_p be the predecessor of s' on this path. By the induction hypothesis,

$$\begin{aligned} &g^*(s) + (\epsilon - 1)c_m k(s) \\ &= g^*(s_p) + c(s_p, s') + c^*(s', s) + (\epsilon - 1)c_m k(s) \\ &\geq g(s_p) + c(s_p, s') + h(s', s) + (\epsilon - 1)c_m (k(s) - k(s_p)) \\ &\geq g(s') + h(s', s) + 2(\epsilon - 1)c_m \\ &\geq g(s') + wh(s', s) + (1 - w)c_l + 2(\epsilon - 1)c_m \\ &\geq g(s') + w(h(s') - h(s)) + (1 - w)c_l + 2(\epsilon - 1)c_m \\ &= g(s) + f(s') - f(s) + (1 - w)c_l + 2(\epsilon - 1)c_m \\ &= \text{bound}(s) \end{aligned}$$

□

References

Klein, P. N., and Subramanian, S. 1997. A randomized parallel algorithm for single-source shortest paths. *Journal of Algorithms* 25(2):205–220.