Type-WA*: Using Exploration in Bounded Suboptimal Planning

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1 Paper Reflection

The problem that the paper *"Type-WA*: Using Exploration in Bounded Suboptimal Planning"* seeks to address is the degradation of performance for Weighted A* (WA*) in uninformative heuristic regions (UHRs), where the heuristic fails to provide useful guidance for progression. While popular methods such as random exploration can assist Greedy Best-First Search (GBFS) in escaping UHRs, these methods cannot be directly applied to WA* without compromising the solution quality guarantees.

The main contribution of the paper is the introduction of the Type-WA* (TWA*) algorithm, a novel bounded suboptimal planning algorithm that integrates type-based exploration into Weighted A* (WA*). This algorithm is guaranteed to find w-admissible solutions, assuming the heuristic used is admissible. TWA* employs an (h, g) type system, where two nodes n and n' are in the same partition if and only if $h(n) = h(n')$ and $g(n) = g(n')$. This type system ensures that any two nodes n and n' with different f-values (i.e., $f(n) \neq f(n')$) are in distinct partitions.

In TWA*, the open list is ordered by f_w for WA*-like expansions, while the focal list contains nodes whose f-value is less than or equal to $w \times f_{min}$, where f_{min} is the minimum f-value in the open list. The focal list is further partitioned into buckets based on the type-based system, with the buckets sorted by f-cost. The algorithm alternates between selecting nodes with the minimum f_w values for expansion and exploration steps, where a random bucket is chosen, and a random node is selected from that bucket. This exploration mechanism helps mitigate the weaknesses of WA* in uninformative heuristic regions.

To evaluate the proposed TWA* algorithm, the authors conducted experiments in two benchmark domains: *Blocksworld* and *NoMystery*, as well as instances from the International Planning Competition (IPC). Three different heuristics were tested, including the *merge-and-shrink heuristic* (h^{MS}), the admissible variant of the *landmark count heuristic* (h^{LM}), and the *landmark count heuristic* (h^{LC}).

For the Blocksworld domain, experiments were performed on 100 random instances of the 4-operator Blocksworld problem with 15 blocks. The authors observed that for relatively easy problems, there is little difference with and without exploration. However, for problems that are more difficult for WA* (i.e., those that took longer than 10 seconds to solve), TWA* significantly outperformed WA*, reducing both the solution time and the number of nodes expanded by several orders of magnitude. TWA* also solved more instances than WA* across different weight settings.

In the NoMystery domain, the experiments were based on 100 random instances with 14 packages and 14 locations. Similarly, TWA* solved more instances than WA* and tackled the hardest problems much faster. The authors also noted that increasing w makes problems harder for WA*, while this increase does not significantly impact TWA*'s performance.

For the IPC domains, the authors tested all instances from IPC 2014 and IPC 2018 (optimal track). They observed that TWA* achieved substantially higher coverage than WA* for all three heuristics. The authors also analyzed the normalized solution cost for TWA* (using the h^{MS} heuristic) compared to WA* for $w \in \{2, 3, 10\}$. The solutions found by TWA* generally had higher costs, indicating that TWA* effectively used the allowed suboptimality to solve more problems. To further test this, the authors ran TWA* with $w = 10$ while using $\bar{w} = 2$ for the construction of the focal list. This led to fewer problems being solved than TWA*, but with higher quality solutions, while still outperforming WA*. The authors also explored pure type-based focal exploration and found that while it performed well and even outperformed WA* in some settings, TWA* consistently outperformed both WA* and pure type-based focal exploration.

One area of improvement for this paper is that it could benefit from a deeper analysis of how different heuristics impact the performance of TWA*. The paper could identify specific characteristics of heuristics that lead to poor performance in certain domains and propose strategies to mitigate these issues beyond the addition of exploration.

Finally, two important questions arise. The first concerns why Type-WA* typically takes longer than WA* on problems that both algorithms solve quickly (i.e., in less than $10^0 = 1$ second). This is likely due to the fact that, in Type-WA*, to maintain an accurate f_{min} value, nodes from the lowest f-cost bucket must be removed until an open node is found before selecting a node for exploratory expansion.

The second question pertains to why WA*'s performance sometimes worsens as the weight w increases, and how adding exploration improves performance. Increasing w causes the search to rely more heavily on the heuristic function. If the heuristic suffers from large uninformative heuristic regions (UHRs), increasing w can degrade performance by leading the search into these areas. Adding exploration helps alleviate this issue by allowing the algorithm to escape large UHRs, thus improving performance.