The AAAI-17 Workshop on
Symbolic Inference and Optimization
WS-17-14

PDDL+ Planning with Temporal Pattern Databases

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Abstract

The introduction of PDDL+ allowed more accurate representations of complex real-world problems of interest to the scientific community. However, PDDL+ problems are notoriously challenging to planners, requiring more advanced heuristics. We introduce the Temporal Pattern Database (TPDB), a new domain-independent heuristic technique designed for PDDL+ domains with mixed discrete/continuous behaviour, non-linear system dynamics, processes, and events. The pattern in the TPDB is obtained through an abstraction based on time and state discretisation. Our approach combines constraint relaxation and abstraction techniques, and uses solutions to the relaxed problem, as a guide to solving the concrete problem with a discretisation fine enough to satisfy the continuous model's constraints.

1 Introduction

Automated planning is continuously evolving to tackle challenging problems emerging from various fields of science. The standardised planning language, PDDL (McDermott et al. 1998), has evolved accordingly to allow modelling of new concepts and constructs, and subsequently enable further research. PDDL+ (Fox and Long 2006) extended the language to include processes and events.

PDDL+ enabled modelling of hybrid systems (mixed discrete/continuous domains), and planning with PDDL+ domains has been gaining substantial research interest in the recent years. Problems set in hybrid systems are notoriously difficult to solve. Non-linear system dynamics, high branching factors, and vast search spaces can render even state-of-the-art heuristic planners ineffective. Hybrid systems have also been the subject of research in Model Checking for many years. Striking similarities between model checking and automated planning allowed symbiotic growth of both fields, through knowledge transfer of approaches and techniques (e.g. (Bogomolov et al. 2014; Bryce et al. 2015)).

One of the approaches successfully used in both planning and model checking is the Pattern Database (PDB)(Culberson and Schaeffer 1998). A Pattern Database is a look-up table indexed by a subset of the state and containing a precomputed heuristic value that reflects the cost of solving the corresponding subproblem. In planning, PDBs are considered one of the most successful classes of heuristics for classical planning problems (Edelkamp 2014), while model checking approaches rely on PDBs for handling hybrid systems.

We build on research conducted in both fields to develop the Temporal Pattern Database (TPDB), a new domain-independent heuristic method that enables tackling complex planning problems containing non-linear dynamics and mixed discrete/continuous behaviour. The TPDB combines time and state abstraction with constraint relaxation, and uses the solutions to the relaxed problems as a guide to solving the concrete problems.

To further improve the efficiency and performance, we also introduce the Partial Temporal Pattern Database. It is a downscaled variant of the TPDB, which operates in the same manner, and uses the same mechanics to guide the search as the full TPDB. Our heuristic prunes a substantial part of the search space, reducing the execution time.

We implemented the Temporal Pattern Database heuristic into DiNo (Piotrowski et al. 2016), a discretisation-based heuristic planner, able to cope with non-linear dynamics and full PDDL+ semantics. The new extension is called DiNo-TPDB. To the best of our knowledge, it is the first extension of the PDB heuristic to temporal hybrid planning domains.

We begin by discussing related work in section 2. Next, in section 3, we give a background on DiNo and its discretised setting. Section 4 describes, and formally defines, the Temporal Pattern Database heuristic. Experimental results and comparison against other planners are shown in section 5. Section 6 concludes the paper and describes future research.

2 Related Work

The Pattern Databases (PDBs) are a successful class of abstraction heuristics, originating from classical planning (Culberson and Schaeffer 1998). They have since been used to solve a variety of problems (Edelkamp 2002; 2014; Haslum et al. 2007; Sievers, Ortlieb, and Helmert 2012). While PDBs in planning are applied to propositional domains, research in model checking has concentrated on using PDBs for hybrid systems (Bogomolov et al. 2012; 2013). PDBs in planning applications work by obscuring part of the states' variable set, model checking approaches exploit PDBs by abstracting the continuous state variables.

Over the years, there have been various restricted approaches in planning for dealing with hybrid domains (McDermott 2003a; Penberthy and Weld 1994; Li and Williams 2008; Coles et al. 2012; Shin and Davis 2005; Fernández-González, Karpas, and Williams 2015; Scala et al. 2016), though none of them use PDB heuristics. Furthermore, these planners have significant limitations either in terms of scaling, handling PDDL+ features, or using a different modelling language altogether. More recent attempts at dealing with PDDL+ domains include using SMT solvers such as SMTPlan+ (Cashmore et al. 2016), an efficient planner handling all aspects of PDDL+, though limited to nonlinear polynomials. UPMurphi (Della Penna et al. 2009) can reason with the full PDDL+ feature set and non-linear dynamics but suffers from scalability issues. DiNo (Piotrowski et al. 2016) extends UPMurphi, and alleviates scalability issues with the Staged Relaxed Planning Graph+ heuristic, specifically designed for PDDL+ domains.

Currently, due to the complexity of PDDL+ domains, all planners focus on finding a feasible solution only.

3 PDDL+ Planning through Discretisation

DiNo (Piotrowski et al. 2016) and UPMurphi (Della Penna et al. 2009) are discretisation-based planners, that approximate the continuous dynamics of systems in a discretised model using uniform time steps and step functions. The use of a discretised model and a finite-time horizon ensures a finite number of states in the search for a solution, which can be validated against the original continuous model through the validator VAL (Howey, Long, and Fox 2004).

In order to plan in the discretised setting, PDDL+ models are translated into *finite state temporal systems*, as formally described in the following. The notation is inspired from (Piotrowski et al. 2016).

Definition 1. ***Concrete State***. *Let $P = \{p_1, ..., p_m\}$ be a finite set of discrete variables and $V = \{v_1, ..., v_n\}$ be a set of real variables. A state s is a triple $s = (p(s), v(s), t(s))$, where $p(s) = (p_1(s), ..., p_m(s)) \in \mathbb{Z}^m$ composes the discrete part of the state, $v(s) = (v_1(s), ..., v_n(s)) \in \mathbb{R}^n$ composes the continuous part of the state, and $t(s)$ is the value of the temporal clock in state s. We also denote with $v_i(s)$ ($p_i(s)$ respectively) the value of variable at the i-th position in $v(s)$ ($p(s)$ respectively).*

Here only real variables and temporal clock are discretised, according to the Discretise & Validate approach (Della Penna, Magazzeni, and Mercorio 2012).

Definition 2. $\Delta-$***Action***. *A Δ-action updates the state during the search. It can be of three types: an instantaneous PDDL action, a* snap action *(Long and Fox 2003), or a time-passing action, tp.*

Borrowing from (Hoffmann 2003), we also denote the set of action preconditions as $pre(\Delta a)$, and the set of action effects as $eff(\Delta a)$.

Definition 3. ***Finite State Temporal System (FSTS)***. *Let a Finite State Temporal System $\mathcal{S}$ be a tuple $(S, s_0, \Delta\mathcal{A}, \mathcal{D}, F, T)$ where S is a finite set of states, $s_0 \in S$ the initial state, $\Delta\mathcal{A}$ is a finite set of Δ-actions and $\mathcal{D} = \{0, \Delta t\}$ where Δt is the discretised time step. $F : S \times \Delta\mathcal{A} \times \mathcal{D} \to S$ is the transition function, i.e. $F(s, \Delta a, d) = s'$ iff applying a Δ-action Δa with a duration d to a state s yields a new reachable state s'. T is the finite temporal horizon.*

Note that d can be 0 to allow for concurrent plans and instantaneous actions. In fact, d will equal Δt only in the case of the tp action. The finite temporal horizon T makes the set of discretised states S finite.

A solution to a planning problem (i.e. a trajectory) is a path in the FSTS transition graph from a reachable state, and ending with a goal state. Therefore, a solution to a planning problem is a trajectory starting with the initial state.

Definition 4. ***Trajectory***. *A trajectory, π, in an FSTS $\mathcal{S} = (S, s_0, \Delta\mathcal{A}, \mathcal{D}, F)$ is a sequence of states, Δ-actions and durations ending with a state, i.e. $\pi = s_0, \Delta a_0, d_0, s_1, \Delta a_1, d_1, ..., s_n$ where $\forall i \geq 0, s_i \in S$ is a state, $\Delta a_i \in \Delta\mathcal{A}$ is a Δ-action and $d_i \in \mathcal{D}$ is a duration. At each step i, the transition function F yields the subsequent state: $F(s_i, \Delta a_i, d_i) = s_{i+1}$.*

Given a trajectory π, we use $\pi_s(k), \pi_a(k), \pi_d(k)$ to denote the state, Δ-action, and duration at step k, respectively. The length of the trajectory, based on the number of actions it contains, is denoted by $|\pi|$ and the duration of the trajectory is denoted as $\tilde{\pi} = \sum_{i=0}^{|\pi|-1} \pi_d(i)$ or, simply, as $\tilde{\pi} = t(\pi_s(n))$. All states in any trajectory are reachable from states preceding them in the sequence, more formally we define reachable states in the following.

Definition 5. ***Reachable States***. *Let $\mathcal{S} = (S, s_0, \Delta\mathcal{A}, \mathcal{D}, F, T)$ be an FSTS. A state $s_i \in S$ is reachable from state $s_j \in S$ iff there exists a trajectory π in $\mathcal{S}$ s.t. $\pi_s(k) = s_i$ and $\pi_s(l) = s_j$, where $k \leq l$ and $l \leq T$. Therefore, the finite set of states reachable from state $s \in S$ is denoted $Reach(s)$. Conversely, $Reach^{-1}(s)$ is the set of all state from which s is reachable.*

Following from Definition 1, each state s contains the temporal clock t, and $t(s)$ counts the time elapsed in the current trajectory from the initial state to s. Furthermore, $\forall s_i, s_j \in S : F(s_i, \Delta a, d) = s_j$, $t(s_j) = t(s_i) + d$. Clearly, for all states s, $t(s) \leq T$.

Definition 6. ***Planning Problem***. *In terms of a FSTS, a planning problem $\mathcal{P}$ is defined as a tuple $\mathcal{P} = (\mathcal{S}, G)$ where $G \subseteq S$ is a finite set of goal states. A solution to $\mathcal{P}$ is a trajectory π^* where $|\pi^*| = n, \tilde{\pi} \leq T, \pi^*_s(0) = s_0$ and $\pi^*_s(n) \in G$.*

4 Temporal Pattern Database

Temporal Pattern Database extends the PDB to cope with temporal information and continuous variables.

In Fig.1 we show a graphical representation of TPDB-based planning. Initially, the PDDL+ domain and problem are both discretised, according to the D&V approach, using *time* and *state* abstraction (see Sec. 4.1). Notice that we also use a *goal* and *action relaxation* to avoid mismatches between temporal clocks and the time discretisation (see Sec. 4.1). Then, we synthesise a TPDB for the abstract PDDL+ domain and problem as discussed in Sec. 4.2. Once the

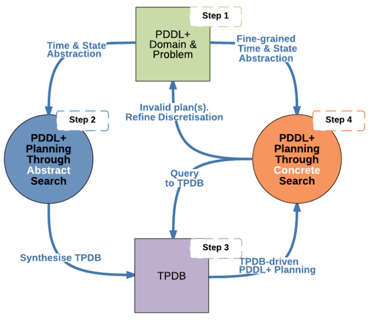
Step 1
PDDL+ Domain & Problem
Time & State Abstraction
Fine-grained Time & State Abstraction
Step 2
PDDL+ Planning Through Abstract Search
Invalid plan(s). Refine Discretisation
Step 4
PDDL+ Planning Through Concrete Search
Query to TPDB
Synthesise TPDB
Step 3
TPDB
TPDB-driven PDDL+ Planning

Figure 1: Outline of TPDB-based Planning

TPDB has been generated, we can solve the original PDDL+ planning problem by performing a concrete search using a fine-grained discretisation Δt. Specifically, the TPDB is queried for each explored concrete state to provide the next promising action which is likely to be on the path to the goal. The action is then applied to the concrete state and the process is repeated for the subsequently explored state. Effectively, the TPDB guides the concrete search to explore only the promising areas of the search space based on solutions found in the relaxed and abstracted setting. Finally, if the solution resulting from the concrete search is not valid, the discretisation should be refined and the process repeated.

4.1 Building the TPDB

The TPDB maintains the simplicity of the look-up table structure and is generated during the preprocessing stage. Search in abstract and relaxed space is conducted, and the results are compiled into the TPDB.

Abstraction. The abstraction is two-fold: time abstraction and state abstraction. Time abstraction works by scaling the concrete time-step Δt up to the abstract time step $\Delta t^{\#}$, using abstraction function ϕ.

Definition 7. ***Time Abstraction****. A time abstraction is a function $\phi : \mathcal{D} \to \mathcal{D}^{\#}$ which scales the time step up, where $\mathcal{D} = \{0, \Delta t\}$ and $\mathcal{D}^{\#} = \{0, \phi(\Delta t)\}$, i.e. $\phi(\Delta t) = c * \Delta t = \Delta t^{\#}$ where $c \in \mathbb{R}_{\geq 1}$ is a scalar constant.*

Time abstraction is used in the FSTS transition function when using the time-passing action, i.e. $F(s, tp, \Delta t^{\#})$. While time abstraction only concerns the discretised time step, the state abstraction function reduces the precision of all continuous variables $v(s)$, where $s \in S$, to a given value.

Definition 8. ***State Abstraction and Abstract State****. The State Abstraction is a function $\psi : S \times \mathbb{R}^+ \to S^{\#}$ where S is a finite set of concrete states, $S^{\#}$ is a finite set of abstracted states and $\mathbb{R}^+$ is the set of positive real numbers. Then an Abstract State $s^{\#} = \psi(s, q)$ s.t. the abstracted values $v^{\#}(s^{\#})$ are computed as follows: $\forall v \in v(s) : v^{\#} = (v + q/2) - ((v + q/2) \bmod q)$.*

In practice, function ψ reduces the precision of real variables $v(s)$ for a concrete state $s \in S$ and $q \in \mathbb{R}^+$ and yields an abstract state $s^{\#} \in S^{\#}$, i.e. $\psi(s, q) = s^{\#}$. For example, applying state abstraction $\psi(s, 0.05)$ to a state s containing a variable $v_1 \in v(s)$, where $v_1 = 12.34567$, yields an abstract state $s^{\#}$ with real variables scaled to precision of 0.05, i.e. $v_1^{\#} = 12.35$. Applying $\psi(s, 2)$ yields the abstracted variable $v_1^{\#} = 12$.

Discretising continuous system dynamics through step functions can sometimes under- or over-approximate the values of continuous variables (depending on the equations). This can be seen in the non-linear generator domain, where in the discretised model, the planner slightly overestimates the amount of fuel added to the generator (compared to values in the continuous model).

A concrete state s and an abstract state $s^{\#}$ are **corresponding** to each other if they agree on the discrete part of their state variables, and the continuous part of $s^{\#}$ equals to the continuous part of $\psi(s, q)$.

Choosing precision for the state abstraction is crucial for the Temporal Pattern Database. On the one hand, choosing a coarser precision for real variables will shrink the size of the TPDB (each abstract state will correspond to a larger number of concrete states). On the other hand, choosing finer precision will make the heuristic estimates more accurate. When choosing the precision value, one should aim to balance the two aspects.

Relaxation. When the TPDB is built, the problem is relaxed. The relaxation is applied to goal conditions and action durations. Both of these relaxation methods are designed to alleviate issues caused by the coarse abstract discretisation.

Goal relaxation is applied to account for the rigid constraints which can cause problems when working with abstract discretisation. The coarse dicretisation can cause certain values to be eliminated from the domains of durative actions and process time-dependent effects.

The following example should clarify the matter. Consider a durative action whose continuous effect is $v_i(s) += \Delta t$, for some numeric variable $v_i(s) \in s$. If v_i is part of the goal condition, then the value of $v_i(s)$ needs to be a multiple of Δt for the problem to be solvable. To compensate for this issue in the abstract space, we set bounds of size $\Delta t^{\#} + 1$ on each numeric goal condition $v(s_G)$ which account for the discrete transitions between states. The value of the concrete numeric goal lies in between the upper and lower bound, i.e. $lb(\overline{s_G}) \leq v(s_G)$ and $ub(\overline{s_G}) \geq v(s_G)$. The size of the bounds was chosen to contain two multiples of $\Delta t^{\#}$, surrounding the concrete goal condition value so that it accounts for both increasing and decreasing effects.

Definition 9. ***Goal Relaxation****. The goal relaxation is a function $\zeta : G \to \overline{G}$ that, for each goal state $s_G \in G$ computes the set of relaxed goal states resulting from s_G by applying the relaxation to each variable of the continuous part as follows $\forall v_i(s_G) \in v(s_G), v(\overline{s_G}) = (v_1(s_G), \ldots, v_i(\overline{s_G}), \ldots, v_n(s_G))$ where $v_i(\overline{s_G})$ ranges within $\{lb(v_i(\overline{s_G})), ub(v_i(\overline{s_G}))\}$ with $lb(v_i(\overline{s_G})) = v_i(s_G) - (v_i(s_G) \bmod \Delta t^{\#})$ and $ub(v_i(\overline{s_G})) = v_i(s_G) + (\Delta t^{\#} - (v_i(s_G) \bmod \Delta t^{\#}))$*

In simple terms, function ζ amends any goal condition on $v_i(s_G) \in v(s_G)$ s.t. any value between the lower bound $lb(v_i(\overline{s_G}))$ and upper bound $ub(v_i(\overline{s_G}))$, satisfies the goal condition on $v_i(s_G)$.

In the case of propositional goal conditions, we relax the numeric preconditions of actions which achieve those goal conditions in the similar manner as Def. 9.

Definition 10. ***Action Precondition Relaxation***. *Extending the ζ function defined in Def. 9, by abuse of notation, we apply the function to the set of actions, such that: $\zeta : \Delta\mathcal{A} \rightarrow \overline{\Delta\mathcal{A}}$. Numeric action preconditions are relaxed such that: if $\exists p_i(s_G) \in p(s_G) \cap eff(\Delta a)$,then $v = \zeta(v), \forall v \in pre(\Delta a)$ with $\Delta a \in \Delta\mathcal{A}$ and $s_G \in G$.*

Example: Let p_k be a propositional fact in the goal state s_G, i.e. $p_k \in p(s_G)$, and let a_i be a Δ-action with precondition $pre(a_i) = \{v_j = 10\}$ and effect $eff(a_i) = \{p_k\}$. Then, the action precondition relaxation would modify the precondition of a_i such that $pre(a_i) = \{v_j \geq lb(v_j), v_j \leq ub(v_j)\}$.

Action Duration Relaxation. Another issue which arises from a coarse time discretisation, is to do with durative actions. A coarse abstract time step $\Delta t^{\#}$ can render some action a inapplicable if its fixed duration $d(a) \notin \mathcal{D}^{\#}$, or if its maximum flexible duration $d^{max}(a) < \Delta t^{\#}$.

Definition 11. ***Action Duration Relaxation***. *The action duration relaxation is an action which expands the domain of action durations in the abstract space $\eta : \mathcal{D}^{\#} \rightarrow \overline{\mathcal{D}^{\#}}$, where $\mathcal{D}^{\#} = \{0, \Delta t^{\#}\}$ and $\overline{\mathcal{D}^{\#}} = \mathcal{D}^{\#} \cup \mathbb{R}^{+}$.*

Simply, action durations are no longer bound to multiples of $\Delta t^{\#}$ but can have any duration, subject to $d(a) \leq d^{max}(a)$.

4.2 Temporal Pattern Database

Using the abstraction and relaxation functions, we define the Abstract FSTS and the Abstract Planning Problem which, in turn, form the basis of the Temporal Pattern Database. The Abstract FSTS and Abstract Planning Problem are, in fact, both *relaxed* and *abstracted* by functions ζ, η, ϕ, and ψ.

Definition 12. ***Abstract FSTS***. *Let $\mathcal{S} = (S, s_0, \Delta\mathcal{A}, \mathcal{D}, F, T)$ be a FSTS, then an Abstract FSTS $\overline{\mathcal{S}^{\#}}$ is a tuple $(S^{\#}, s_0, \overline{\Delta\mathcal{A}}, \overline{\mathcal{D}^{\#}}, F^{\#}, T)$ where $S^{\#}$ is a finite set of abstract states under state abstraction ψ, s_0 is the initial state, $\overline{\Delta\mathcal{A}}$ is a finite set of Δ-actions under relaxation ζ, and $\overline{\mathcal{D}^{\#}} = \{0, \Delta t^{\#}\} \cup \mathbb{R}^{+}$ is a set of relaxed abstract action durations. $F^{\#} : S^{\#} \times \overline{\Delta\mathcal{A}} \times \overline{\mathcal{D}^{\#}} \rightarrow S^{\#}$ is a transition function, and T is a finite temporal horizon.*

Definition 13. ***Abstract Planning Problem***. *Let $\mathcal{P} = (\mathcal{S}, G)$ be a planning problem, then an abstract planning problem is a tuple $\overline{\mathcal{P}^{\#}} = (\overline{\mathcal{S}^{\#}}, \overline{G})$, where $\overline{\mathcal{S}^{\#}}$ is an Abstract FSTS, and $\overline{G} = \zeta(g)$ is the relaxed set of goal conditions under relaxation ζ.*

The Temporal Pattern Database is a structure which maps abstract states to actions applicable in the relaxed state space. A TPDB is built by using the Abstract FSTS and transition function $F^{\#}$ to generate the subsequent abstract states, until the abstract goal state is found, or the finite temporal horizon T is reached. The latter meaning that the bounded abstract problem is unsolvable with the current parameters, prompting a refinement of the abstract time step $\Delta t^{\#}$ and/or an increase of the temporal horizon.

Formally, we define the TPDB as follows[1].

Definition 14. ***Temporal Pattern Database (TPDB)***. *Let $\overline{\mathcal{P}^{\#}} = \{\overline{\mathcal{S}^{\#}}, \overline{G}\}$ be an abstract planning problem, $\overline{\mathcal{S}^{\#}} = (S^{\#}, s_0, \overline{\Delta\mathcal{A}}, \overline{\mathcal{D}^{\#}}, F^{\#}, T)$ be an Abstract FSTS, and $\overline{\mathcal{R}^{\#}} = Reach(s_0) \cap \bigcup_{\overline{s_G} \in \overline{G}} Reach^{-1}(\overline{s_G})$. Then a Temporal Pattern Database is a finite map TPDB, from $\overline{\mathcal{R}^{\#}}$ to $\overline{\Delta\mathcal{A}}$ such that $\forall s^{\#} \in \overline{\mathcal{R}^{\#}}$ there exist k, such that $\pi_s(k) \in \overline{G}$, and a trajectory π such that $\pi_s(0) = s^{\#}$, $\forall t < k \; \exists \overline{d^{\#}} \in \overline{\mathcal{D}^{\#}} : \pi_s(t+1) = F^{\#}(\pi_s(t), TPDB(\pi_s(t)), \overline{d^{\#}})$ and $\tilde{\pi} \leq T$.*

Informally, a TPDB stores all abstract state-action pairs which exist on some trajectory to the relaxed goal.

4.3 Partial TPDB

PDDL+ planning problems often have high branching factors and long temporal horizons. Exhaustively traversing the search space to build the full TPDB, even with a coarse discretisation and relaxation, can be very time- and memory-consuming. The added overhead is in most cases redundant, as most of the search space is never explored during the concrete search, thus the TPDB is never queried for the majority of its elements. Because we are only concerned with finding a feasible solution to the given problems, generating a full TPDB is often unfeasible, as the time to build the TPDB can disproportionately outweigh the run time of concrete search.

A solution to this issue is generating a Partial Temporal Pattern Database, pruning parts of the abstract search space and significantly reduces TPDB build time. Intuitively, once a goal state s_G has been reached (i.e. $s_G \in Reach(s0)$), a partial TPDB can be synthesised by collecting all the encountered (state,action) pairs, reachable from s_0, that are on some path to *the single goal state* s_G (i.e. $Reach^{-1}(s_G)$).

It can be seen as a river, that originates from a single source s_0, then it grows by branching in several streams, it receives water from several tributaries, and finally ends in the mouth (i.e., goal state s_G). A partial TPDB would consider all streams generated from the source that are able to reach the mouth. Conversely, all the tributaries originating from outside the river would be discarded.

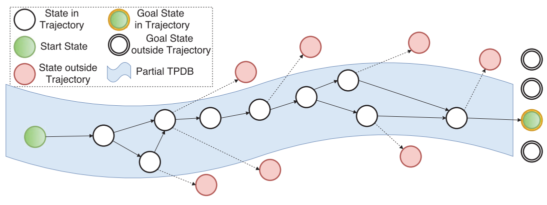

Figure 2: Building the Partial TPDB

We generate the Partial Temporal Pattern Database by limiting the abstract search to one relaxed goal state $\overline{s_G} \in \overline{G}$,

[1]Our TPDB notation was inspired by (Della Penna, Magazzeni, and Mercorio 2012)

and by accepting subsets of the intersection of the set of abstract states reachable from the initial state ($Reach(s_0)$), and the set of states from which one goal state is reachable ($Reach^{-1}(\overline{s}_{\overline{G}})$).

Definition 15. ***Partial Temporal Pattern Database (TPDB).*** *Let TPDB= $\{(\overline{\mathcal{R}\#}, \overline{\Delta\mathcal{A}})\}$ be a Temporal Pattern Database as in Def. 14, then a* Partial *Temporal Pattern Database TPDB$_{part}$ $= \{(\overline{\mathcal{R}\#}_{part}, \overline{\Delta\mathcal{A}})\}$ is a map from $\overline{\mathcal{R}\#}_{part}$ to $\overline{\Delta\mathcal{A}}$ where $\overline{\mathcal{R}\#}_{part} \subseteq (Reach(s_0) \cap Reach^{-1}(\overline{s}_{\overline{G}}))$, s_0 is the initial state and $\overline{s}_{\overline{G}} \in \overline{G}$ is a* single *goal state.*

In the TPDB implementation in DiNo, Depth-First Search algorithm (DFS) is used to determine the goal state for which a Partial TPDB will be generated.

4.4 Concrete search with TPDB guidance

The concrete search algorithm is guided by the TPDB generated in the preprocessing stage. The TPDB is queried for every dequeued state. Each of these states is abstracted (using state abstraction) and passed to the TPDB to find a corresponding abstract state and a suggested action. There are 3 possible outcomes when querying the TPDB:

1. Time-passing (*tp*) is returned, Pruning Jump is performed.
2. A Δ-action is returned (other than *tp*).
3. No action is returned, in which case BFS is executed.

The entire algorithm for the full concrete search through TPDB guidance is shown in Alg. 4.1. For sake of completeness, we also provide the workflow of point 2 in Fig. 3, where the TPDB returns a valid Δ-action.

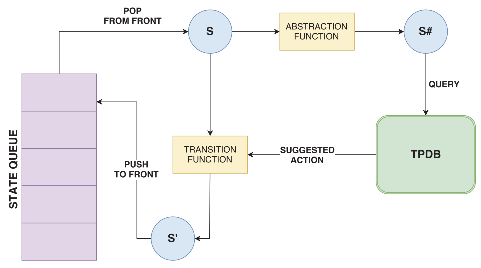

Figure 3: Process of generating new states via TPDB (in concrete search)

Pruning Jump. Pruning Jump is a mechanism used in conjunction with the TPDB to skip parts of the search space which are likely to yield unpromising states. Rather than exploring the generated states and assessing their heuristic values, the search algorithm chooses to advance time. Pruning Jump is triggered by the suggestion from TPDB (line 3 in Alg. 4.1). If the TPDB answers a query with the time-passing action (line 8), the Pruning Jump is executed. It iteratively advances time in the concrete search by a total duration of abstract time step $\Delta t^{\#}$ (line 10). Time passing is applied in increments of the concrete time step Δt, on the previously generated state (line 11) as, due to coarse discretisation, it is possible for an adverse happening, missed

Algorithm 4.1: Concrete Search Algorithm with Pruning Jump and TPDB guidance

```
Data: $s \in S$ = Currently explored state;
      $a \in \Delta\mathcal{A}$ = $\Delta$-action;
      $tp \in \Delta\mathcal{A}$ = time-passing $\Delta$-action;
      $isValid(s)$ = true if no constraints are violated in $s$;
1  $Q := \emptyset s := s_0$;
2  while $s \notin G$ do
3      $a_{best} := TPDB(s)$  ▷ returns suggested action querying the TPDB;
4      if $isValid(s)$ then
5          if $a_{best} = \emptyset$ then
6              for $s_{succ} \in Successors(s)$ do
7                  $enqueue(Q, s_{succ})$;
8          else if $a_{best} = tp$ then
9              $i := 0$;
10             while $i < \Delta t^{\#}$ do
11                 $s := F(s, tp, \Delta t)$;
12                 if $\neg isValid(s)$ then
13                     break;
14                 $enqueueFront(Q, s)$;
15                 $i := i + \Delta t$;
16         else
17             ▷ Generate state through TPDB suggested action;
18             $s := F(s, a_{best}, 0)$;
19             $enqueueFront(Q, s)$;
20     $s := dequeue(Q)$;
```

in abstract search, to occur in concrete search (e.g. an event prohibiting achieving goal conditions). Thus after each transition of Δt, a validity check is carried out on the resulting state s' (line 12). If the goal state is no longer reachable, the Pruning Jump stops (line 13) and the search restarts from the last enqueued state (lines 20 & 2). States generated during each iteration of the Pruning Jump are added to the front of the queue (line 14), helping to avoid lengthy backtracking.

In essence, if the TPDB indicates that time-passing action is the most promising from the current state s, and no adverse happenings occur between the corresponding abstract state $s^{\#}$ at time $t(s^{\#})$ and the subsequent abstract state $s'^{\#}$ at time $t' = t(s^{\#}) + \Delta t^{\#}$, the time can be advanced by the abstract time discretised variable $\Delta t^{\#}$ in the concrete search. The number of iterations in a Pruning Jump is determined by the duration of the abstract and concrete time steps, i.e. Number of iterations $= \Delta t^{\#}/\Delta t$.

Effectively, the Pruning Jump acts as an adaptive time discretisation mechanism which helps in mitigating state explosion by skipping unpromising areas of the space.

Back-up Search Strategy. As a back-up strategy, if no corresponding state is found in the TPDB, the search is forwarded through breadth-first search, querying the TPDB for every visited state. If a corresponding state is found, the search is continued through the suggested actions again.

The back-up search strategy has been devised to account for situations when the TPDB fails to provide a feasible next step. This can occur for three reasons:

- TPDB-suggested action is inapplicable in concrete search

	LINEAR GENERATOR					NON-LINEAR GENERATOR				ADVANCED LINEAR SOLAR ROVER			ADVANCED NON-LINEAR SOLAR ROVER			POWERED DESCENT			VERTICAL TAKE-OFF			CAR		
	DiNo-T	**DiNo-S**	**SMTPlan+**	**POPF**	**UPM**	**DiNo-T**	**DiNo-S**	**SMTPlan+**	**UPM**	**DiNo-T**	**DiNo-S**	**UPM**	**DiNo-T**	**DiNo-S**	**UPM**	**DiNo-T**	**DiNo-S**	**UPM**	**DiNo-T**	**DiNo-S**	**UPM**	**DiNo-T**	**DiNo-S**	**UPM**
1	0.38	0.34	0.04	0.01	140.50	0.54	3.62	0.04	X	0.38	0.54	X	0.40	298.44	X	0.56	0.68	0.18	0.46	130.34	9.86	1.04	24.02	0.34
2	0.34	0.40	0.04	0.01	X	0.88	0.78	0.06	X	0.44	140.24	X	0.42	X	X	0.58	1.04	0.74	0.32	X	202.22	1.72	90.34	0.74
3	0.36	0.50	0.04	0.05	X	1.50	2.86	0.09	X	0.42	X	X	0.42	X	X	6.30	1.88	2.98	0.32	X	X	2.72	191.76	1.16
4	0.38	0.60	0.05	0.41	X	2.44	59.62	0.18	X	0.48	X	X	0.50	X	X	27.48	3.52	7.18	0.34	X	X	3.50	240.74	1.64
5	0.38	0.74	0.08	6.25	X	3.62	1051.84	0.40	X	0.44	X	X	0.46	X	X	40.46	2.88	30.08	0.34	X	X	3.64	286.82	1.96
6	0.38	0.88	0.12	120.49	X	5.78	X	0.95	X	0.54	X	X	0.50	X	X	97.46	3.14	126.08	0.36	X	X	5.46	359.72	2.10
7	0.38	1.00	0.21	X	X	8.90	X	2.34	X	0.56	X	X	0.54	X	X	522.44	5.26	322.16	0.36	X	X	7.70	365.18	2.46
8	0.36	1.16	0.43	X	X	13.94	X	5.79	X	0.70	X	X	0.72	X	X	444.78	3.82	879.52	0.38	X	X	7.78	405.90	2.44
9	0.36	1.38	0.96	X	X	25.02	X	14.09	X	0.56	X	X	0.56	X	X	527.32	1.58	974.60	0.40	X	X	7.80	461.60	2.60
10	0.36	2.00	2.41	X	X	X	X	34.53	X	0.68	X	X	0.68	X	X	535.18	2.26	X	0.42	X	X	10.04	389.82	2.44
11	0.40	1.84	7.46	X	X	-	-	-	-	0.70	X	X	0.72	X	X	10.06	11.24	X	-	-	-	-	-	-
12	0.40	2.06	28.58	X	X	-	-	-	-	0.66	X	X	0.66	X	X	9.72	42.24	X	-	-	-	-	-	-
13	0.40	2.32	107.57	X	X	-	-	-	-	0.70	X	X	0.70	X	X	X	14.90	X	-	-	-	-	-	-
14	0.40	2.46	503.80	X	X	-	-	-	-	0.74	X	X	0.72	X	X	X	61.94	X	-	-	-	-	-	-
15	0.38	2.88	X	X	X	-	-	-	-	0.78	X	X	0.78	X	X	X	19.86	X	-	-	-	-	-	-
16	0.42	2.94	X	X	X	-	-	-	-	0.82	X	X	0.82	X	X	X	80.28	X	-	-	-	-	-	-
17	0.40	3.42	X	X	X	-	-	-	-	0.88	X	X	0.66	X	X	X	2.94	X	-	-	-	-	-	-
18	0.40	3.54	X	X	X	-	-	-	-	0.90	X	X	0.92	X	X	X	X	X	-	-	-	-	-	-
19	0.42	3.76	X	X	X	-	-	-	-	0.98	X	X	0.94	X	X	X	X	X	-	-	-	-	-	-
20	0.42	4.26	X	X	X	-	-	-	-	1.16	X	X	0.92	X	X	X	X	X	-	-	-	-	-	-

Table 1: Run time in seconds for each problem in our test suite (”X” - planner ran out of memory). Labels: DiNo-T = DiNo with Partial TPDB, DiNo-S = DiNo with SRPG+, UPM = UPMurphi

- Discrepancies in continuous state variables, larger than the state abstraction (ψ) value, between the abstract states in the TPDB and the abstracted concrete states.
- Triggered events and processes, uncaught in the abstract search due to coarse discretisation, changed the state variable values beyond the scope of variables in the TPDB.

In those cases, uninformed search (BFS) is applied until a new concrete state, with a corresponding abstract state in the TPDB (or the goal), is found (lines 5-7 in Alg. 4.1).

Because of the discretised search space and the temporal horizon, the DiNo-TPDB search is complete (subject to Δt).

5 Evaluation

We evaluate the Temporal Pattern Database implementation, and compare the results against other planners capable of handling the same class of PDDL+ domains. This includes DiNo-SRPG+, UPMurphi, and SMTPlan+. For the Linear Generator, we also compare against POPF (Coles et al. 2010) since it can handle the sub-class of PDDL+ required for this domain. For DiNo-TPDB, DiNo-SPRG+ and UPMurphi, the concrete search was conducted under discretisation 1, for all domains. For the abstract search in DiNo-TPDB, the abstraction settings are as follows: Car - $\Delta t^{\#} = 4$, $\psi = 4$; Powered Descent - $\Delta t^{\#} = 2$, $\psi = 4$; Vertical Take-Off - $\Delta t^{\#} = 5$, $\psi = 5$. For all other domains: $\Delta t^{\#} = 10$, $\psi = 5$. The values were based on default UPMurphi/DiNo-S settings. We used the partial TPDB for our heuristic guidance. Tab. 1 shows the results of experiments. Run times for DiNo-TPDB are the combined times of the concrete search and generating the TPDB. All results were obtained on a machine with 8-core Intel i7 CPU, 8GB RAM and Ubuntu 14.04 OS. Where possible, the solutions were validated by VAL. For Powered Descent and Vertical Take-Off, the validation was done via ad-hoc scripts, as system dynamics equations proved too complex for VAL. All test domains are available at https://goo.gl/CFAybW.

Generator. The generator domain (Howey and Long 2003) is a well-established test domain for PDDL+ planners. There are two versions of the domain, linear and non-linear. In the linear version, the generator’s fuel level increases linearly when refueling, whereas the non-linear version of the domain models the flow rate using Torricelli’s Law.

Advanced Solar Rover. The Advanced Solar Rover is an extended version of the Solar Rover introduced in (Piotrowski et al. 2016). In comparison, the advanced version increases the role of batteries in the domain, they can be used more often, and some of the problem instances can actually be solved using batteries alone, rather than solely relying on the future *sunexposure* event to provide energy for the rover. This increases the branching factor and the search space.

Vertical Take-Off. Vertical Take-Off domain models the initial stages of flying a tilt-wing rotor plane. The plane has to lift off and transition into fixed-wing flight above a given altitude and distance from the take-ff point without crashing. The plane can tilt its wings relative to the fuselage, which affects the rate of change in the plane’s horizontal and vertical velocity, the latter is also affected by gravity at all times.

Powered Descent. The domain (Piotrowski et al. 2016) models a lunar descent module making a controlled landing on a given celestial body without crashing (modelled using Tsiolkovsky Rocket Equation (Turner 2008)).

Car. The Car domain (Fox and Long 2006) models an vehicle which has to accelerate and travel a precise distance before coming to a complete stop.

The results show that the partial TPDB heuristic enriches DiNo, and allows it to solve more constrained and complex problems. We notice that DiNo-TPDB does particularly well with domains heavily relying on the Theory of Waiting (McDermott 2003b). In those cases the Pruning Jump significantly prunes the search space, improving the performance. Overall, DiNo-TPDB either outperforms or is competitive on all domains in our test suite. DiNo-TPDB outperforms its predecessor (DiNo-SRPG+) on all but one test domain.

However, DiNo-TPDB needs improvement for the Powered Descent and Car domains. Powered Descent is very time-sensitive and there are major discrepancies between concrete and abstract states in the TPDB, inducing significant backtracking. In the car domain, the numeric values have very different rates of change, generating mismatches between theoretically corresponding states. As a result, DiNo-TPDB makes heavy use of the back-up strategy.

6 Conclusion

We presented Temporal Pattern Database (TPDB), a novel domain-independent heuristic capable of handling complex non-linear PDDL+ models exhibiting both discrete and continuous behaviour. The TPDB stores pairs of abstract states and actions, and uses a solution to the abstracted and relaxed version of the original problem, as guidance to solving the concrete problem. We have also introduced the Partial TPDB, a scaled down variant of the TPDB. We have empirically shown that the DiNo-TPDB is competitive on benchmark domains and outperforms other PDDL+ planners. The heuristic combines and extends approaches used in automated planning and model checking, and it is an important step in PDDL+ planning. Future research will focus on automating the process of selecting the discretisation and abstraction settings.

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