Virtual Surfaces and Attitude Aware Planning and Behaviours for Negative Obstacle Navigation*

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Abstract—This paper presents an autonomous navigation system for ground robots traversing aggressive unstructured terrain through a cohesive arrangement of mapping, deliberative planning and reactive behaviour modules. All systems are aware of terrain slope, visibility and vehicle orientation, enabling robots to recognize, plan and react around unobserved areas and overcome negative obstacles, slopes, steps, overhangs and narrow passageways. This is the first work to explicitly couple mapping, planning and reactive components in dealing with negative obstacles. The system was deployed on three heterogeneous ground robots for the DARPA Subterranean Challenge, and we present results in Urban and Cave environments, along with simulated scenarios, that demonstrate this approach.

I. INTRODUCTION

Negative obstacles (cliffs, ditches, depressions) pose a difficult problem for autonomous navigation in unstructured environments, as is reported from deployments of highly capable vehicles in natural terrain, such as Crusher [1] or the Legged Squad Support System (LS3) [2]. Negative obstacles are difficult to detect from vehicle mounted sensors as the near-field terrain obfuscates a drop, slope and/or trailing rising edge. Compared to a positive obstacle, occlusions and viewing angles result in fewer pixels-on-target [3], which in turn reduces the effective detection range, often to within the stopping distance of ground vehicles moving at any appreciable speed.

For vehicles capable of autonomously traversing extreme ramp angles (i.e. greater than 45 degrees), even slowly approaching a negative obstacle requires significant care in planning and sensor placement to ensure robust navigation: the obstacle must be approached from an optimal angle, so the system can observe down and determine if the terrain is a traversable ramp, or a fatal discontinuity. There are few examples of robotic systems capable of detecting and traversing negative obstacles in unstructured terrain, such as [4], wherein the system can both detect and safely traverse gaps in the terrain by reasoning about the boundaries of the gap or unobserved region.

In this paper, we adopt a virtual surface concept to estimate the best case slope within occluded regions of the map as shown in Figure 1. These virtual surfaces are used when estimating traversal cost using the footprint of the robot. By updating virtual surfaces in real-time, while continuously planning and collecting data, negative obstacles can be safely approached and avoided if they are found to be unsafe. The primary contributions of this paper are:

1) An open-source 3D probabilistic voxel occupancy map [5] that uses ray tracing for virtual surface construction, suitable for real-time robot navigation, and relevant data sets for evaluation
2) A fast planner based on Hybrid A* [6] which uses the vehicle footprint to estimate and constrain the roll and pitch of the vehicle over the planned path. The planner also includes constraints to approach virtual surfaces (i.e. unobserved areas) from an optimal angle.
3) Relevant field trial results from urban and cave environments, demonstrating the ability to navigate negative obstacles in extreme terrain.

The rest of the paper is structured as follows. We present literature reviews for heightmap generation, negative obstacle detection, and path planning in Section II. Section III addresses methodologies proposed in this paper including the sensor pack, mapping and heightmap generation, local costmap generation, path planning, and behaviour selection

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https://data.csiro.au/collections [will be available soon]
followed by experimental results in both real-world subterranean and simulated environments in Section IV. Lessons learned from extensive field experiments are shared and discussed in Section V. Lastly, Section VI summarises and presents feasible outlooks of the proposed work.

II. RELATED WORK

In this section we present literature reviews for occupancy map-based heightmap representation, negative obstacle modelling, and unmanned ground vehicle (UGV) path planning.

In order to effectively handle negative and positive obstacles it is important to have an efficient and precise heightmap representation. This encapsulates each grid cell’s height with respect to an odometry coordinate to be used for estimating inclinations and terrain properties.

Octomap [7] is a popular library that makes use of probabilistic and 3D octree representation for memory efficiency. Octomap has had numerous successful deployments for various applications including underwater [8], flying [9], walking [10] and ground [11] robots. Drawing inspiration from [7], we implemented a computationally efficient heightmap generation algorithm [5] extracted from a 3D voxel occupancy map computed in GPU and only considered object detection within a predefined local area. Technical detail is presented in section III-B.

Positive obstacles such as boxes or other robots can be effectively detected by computing eigenvectors of a small patch from the estimated heightmap [12] and the current vehicle’s state, such as pose and surrounding meta information. In contrast, negative obstacles are often unobservable (e.g. cliffs or ditches) and are inferred from gaps in the map, thus detection using geometric information is prevalent. Often depth data is accumulated into a voxel map, unobserved cells are computed and then classified as obstacles based on adjacent observed voxels.

Stereo vision [2] and RGBD [13] has been demonstrated in extreme terrains, using ray tracing over a 2D map to compute the minimum possible slope and maximum (downward) step height of unobserved areas. Lidar sensors have been used [14], [15] with 3D ray tracing for determining occlusion and classifying obstacles using nearby observed voxels [16] or classifying the points below the ray path [17] with heuristics and SVM. Our work instead estimates a 3D virtual surface inside the occlusion, as opposed to using just the edges of the occlusion for making determinations. In addition our determination of obstacle fatality includes the vehicle footprint and is orientation dependent.

Lidar based detection is also achieved in 2D height maps [18] by propagating information from all nearby observed cells to infer the unobserved terrain. Image based approaches are a far less common method for detecting negative obstacles. There do not appear to be any RGB based methods, but thermal imagery has been exploited by observing that negative depressions remain warmer than surrounding terrain at night [3]. This thermal intensity data was later used in combination with stereo vision and geometry based thresholds to further increase detection range [19].

Finally, a motion planning algorithm uses the heightmap and costmap (including positive and negative obstacles) to compute a trajectory to safely reach a goal. Motion planning is an important building block for autonomous vehicles so there has been active research on this topic for decades [20]. Motion planning often takes into account not only geometric details of paths (e.g. Dijkstra [21] or \( A^* [22] \)) but also the vehicle’s kinematic constraints in order to generate feasible trajectories [23]. In this paper we used a hybrid \( A^* [24] \) planner which is a variant of the \( A^* \) algorithm that considers the vehicle’s kinematic constraints. The planner computes a desired trajectory using a simplified vehicle configuration evaluation method (see [25] for a more capable method) to ensure the vehicle is capable of traversing the terrain below it. The planner is used to plan onto virtual surfaces at a range, and has an appropriate sensor configuration such that fatality of negative obstacles can be determined if approached head on before traversal.

III. METHODOLOGIES

A. Sensing and SLAM payload

The sensing payload used in all experiments described here consists of a tilted Velodyne VLP-16 lidar on a rotating, encoder tracked mount, a Microstrain CV5-25 IMU and a custom timing board used for time synchronisation between sensors. This 0.5-Hz rotating lidar mount improves sensor coverage around the vehicle, while the tilt angle improves visibility of the ground in front of the vehicle and the lidar coverage density and diversity. The payload includes built-in compute consisting of a Jetson Xavier and is used to run custom SLAM software [26]. This payload is colloquially referred to as the “Catpack” as shown in Figure 2. The Catpack is placed near the front of the vehicle, ensuring a downward field of view greater than the maximum ramp angle the vehicle can traverse.

The Catpack publishes odometry and a raw lidar point cloud as ROS [27] data streams. The pack also localises the points in the point cloud to account for the encoder rotation and lidar orientation. As a consequence, these points are published in the vehicle frame at approximately 290k points per second, depending on the environment, while the local odometry pose is updated at 100Hz with higher accuracy poses generated in the data stream at approximately 4Hz.

http://wiki.ros.org/octomap
B. Mapping and heightmap generation

The heightmap used to generate a base costmap is extracted from a 3D probabilistic voxel occupancy map. The occupancy map [5] is generated from the combination of 3D lidar points and the local odometry output of the SLAM solution. Each ray is integrated into the occupancy map using a technique which supports normal distribution transforms such as described in [28], with these calculations performed in GPU. Each voxel is classified as being either occupied or free with a default state of unobserved. The map is generated at a 10cm voxel resolution.

Since the occupancy map is generated from local SLAM odometry, the map is vulnerable to global misalignment errors. That is to say, this map does not consider any global optimisations such as those enacted by loop closure algorithms. This is addressed by only maintaining the occupancy map locally around the vehicle (~10m × 10m) where misalignment errors will not be significant.

We assume the map is vertically aligned with the z-axis when generating the heightmap and examine individual voxel columns within the occupancy map. It is during heightmap generation that we add an additional voxel classification, virtual surface voxels, which occur at the interface between free and unobserved space. Specifically, a virtual surface classification is assigned to free voxels which have an unobserved voxel immediately below. A virtual surface represents a best case surface in regions which are shadowed in the map and cannot be adequately observed. Virtual surface voxels are only used when there are no occupied voxel candidates within the search constraints of a column.

In addition to the voxel classification, we also impose a clearance constraint to ensure there is a vertical space large enough for the vehicle to fit through. For this constraint we ensure there are sufficient free or unobserved voxels above each candidate voxel to meet the clearance constraint. Three columns considered for heightmap generation are shown in Figure 3.

Virtual surfaces are a key input to detecting negative obstacles. A virtual surface is any region of voxels in the heightmap consisting of virtual voxels as described above. A virtual surface represents a region of observational uncertainty and the best case slope for that region. Such surfaces will often come about from shadowing effects in sensor observations, but will also occur when real surface observations cannot be made such as around black bodies and water. Various scenarios can be seen in Figure 4 where virtual surfaces are generated for a downward slope. As the vehicle approaches the edge of the slope, real observations may be made and a real surface can be generated in the heightmap.

Figure also shows two other factors that impact observations of negative obstacles:

- the downward field of view is much better in front of the robot because the sensor is closer to the front edge of its body;
- the maximum steepness of the downward slope that a robot is able to observe depends on the distance between the sensor and the edge of the slope as well as the height of the sensor.

Figures 4 and 5 highlight the uncertainty inherent with using virtual surfaces: they are by definition an upper bound for the surface beneath them. In Figure 5 a virtual surface is initially generated when the vehicle is too far away from the edge to be able to observe the slope beyond it. As the vehicle approaches the edge, the slope of the virtual surface increases until the real slope is directly observed. There is a limit to the downward field of view, as described in Figure 4. If the slope is steeper than the best downward field of view then the virtual surface will continue to increase in steepness until it reaches that limit and no real observation of the slope will ever be made. The conclusion drawn is that a virtual surface cannot be confirmed as a negative obstacle until the vehicle is in close proximity to the potential surface and has sufficient downward field of view.

C. Costmap generation

Occupancy Homogeneous Map (OHM [5]) produces a 2.5D heightmap that labels each cell as either real (observed), virtual (best case inferred) or unknown. Within this heightmap it is possible to identify obstacles that cannot be traversed in any possible way (e.g. the walls of a hallway). These obstacles are identified and labelled in the costmap.
The costmap contains the same information as the heightmap but with additional labels for non-fatal (possibly traversable) and fatal (definitely non-traversable) cells. Figure 1 shows a visualisation of the costmap on the right where the pink cubes are fatal (including the handrail of the stairs and the edges of the platform), the green cubes are non-fatal (including the ground and the flat surface of the platform) and the orange cubes are virtual (just the shadow of the platform).

Virtual surfaces are treated mostly as if they were real, observed surfaces. This is because they represent the best case slope (shallowest possible) they could contain. If the best case slope is traversable, then they can only be labelled as non-fatal (possibly traversable). If the best case slope is non-traversable then they should be labelled as fatal (definitely non-traversable). The exception to this is when virtual cells are caused by the shadow of positive obstacles such as in Figure 6. In this case the virtual surface should be left as non-fatal to allow for planning around the corner. For this reason, all virtual cells are labelled as non-fatal. Only the upper (higher elevation) end of slopes between cells are labelled as fatal. As a result, fatally steep virtual surfaces only lead to fatal costing where the virtual surface interfaces with real observations of a surface higher than them. This is a good description of the upper edge of a negative obstacle.

We used the GridMap [29] library to arrange a series of filters to generate the costmap. Minor changes to GridMap were made in order to load parameters differently and make minor optimisations. The filter used to identify fatal obstacles was similar to the one used in [30] with an added step to remove small concavities that the vehicle can easily traverse and to use vertical sections in three directions instead of four.

D. Hybrid A*

We have implemented a variant of the hybrid A* algorithm [6] to generate kinematically feasible paths that handle the nearby obstacles and virtual surfaces appropriately. This is an A* path planner applied to the 3D kinematic state space of the robot. The algorithm inputs are the costmap, current robot position, a goal configuration \( q_g = (x, y, \psi) \in \mathbb{R}^3 \) and a covariance which describes the tolerance of the goal.

Our hybrid A* is a heavily modified implementation based on [24]. It dynamically generates a search graph based on a limited set of motion primitives that define the vehicle’s motion constraints. While the search is performed on a discrete 3-dimension configuration space represented as grid, each cell contains the configuration defined in \( \mathbb{R}^3 \) to generate solutions that are not aligned to the grid.

Our contribution to the existing hybrid A* is a custom cost function definition which allows transitioning between adjacent configurations \( q_i, q_j \) taking into account the unstructured environment and the proposed virtual surfaces. It is defined as:

\[
c_{ij} = \left[ \|q_{ix} - q_{jx}\|_P + |q_{iy} - q_{iy}|_P \right] P
\]

where \( p_v, p_w \) are the linear and angular velocity penalties respectively, and \( P \) is the cumulative set of additional penalties, which are platform specific. All individual penalty values in \( P \) are \([1, +\infty) \in \mathbb{R}\). The most relevant of these penalties are:

- **Fatal** penalty. If the footprint of the robot after the transition intersects with any fatal cells in the costmap, then the penalty (and transition cost) is \(+\infty\).
- **Backwards and turning on spot** penalties. If the transition ends with the robot depending on the support of a virtual surface and the motion primitive involves driving backwards or turning on the spot then the penalty is \(+\infty\).
- **Roll** and **pitch** penalties. Both attitude values are estimated using the robot footprint shape and the heightmap. If these are smaller in magnitude than a threshold then the penalty is 1. The penalty increases as the pitch or roll magnitudes increase up to a threshold. If the pitch or roll magnitudes exceed the threshold then the penalty is \(+\infty\). If the pitch is negative (robot facing}
controllers planner Hybrid A* & SLAM

Global feedback

Goals &

Fatal

Odometry, pointclouds, etc.

Velocity

T ested configurations

Compositor

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planning. This is mainly due to high sensing uncertainty and

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The research community has proposed many remarkable and

efficient ways to make an optimal decision given the current

or historical state of a robot [31], [32].

We utilised a rule-based and heuristically modelled be-

aviour selection approach similar to a Finite State Machine

(FSM) [33]. State transitions are based on heuristically de-

fined behaviour priority. For example, a decollide behaviour

will be activated when a robot determines it is stuck while

attempting to follow a desired trajectory. We define the

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tests but the priority selection can be adapted to different

environments or platforms.

A set of independent behaviours were used to generate ve-

locity commands for the robot to execute. These behaviours

run in parallel and each is designed to be activated for

a specific task or in a specific situation. Each behaviour

constant monitors the current situation and outputs the

velocity the robot should execute (admissibility).

This behaviour system helps the robot handle unknown

and unstructured environments in two major ways. Firstly, if

a behaviour decides it is incapable of performing its task

then control will be handed down to the next behaviour.

Secondly, when a task or situation is encountered that no

existing behaviour can handle, we can identify the need for a

new behaviour. Adding a new behaviour has minimal impact

on the rest of the system which reduces the probability of

regression during development.

The nominal behavior in this system is Path Follow, for

tracking a given input path. The behaviour receives the

input path and the pose of the robot and generates velocity

commands to not only follow the path but also reactively

speed up or slow down the robot based on the delta between

current robot pitch and future desired robot pitch according

to the approaching input path section. Effectively, this sees

robots slow down whilst approaching a path section which

starts to decline, speed up whilst approaching a path section

which starts to incline and corrects robot velocity as it

traverses a sloped path to avoid over rotation due to slip

or obstacles in terrain such as rocks or individual steps in a

staircase. Slowing down when approaching downward slopes

is critical. From a distance, downward slopes are virtual

surfaces in the heightmap. Slowing down makes time for the

sensing and processing of incrementally better observations

that refine the virtual surface or reveal the real surface below

it.

Path follow becomes inadmissible when the robot attempts

movement that causes it to start to tip or roll over past a

certain threshold. The orientation correction behaviour be-

comes admissible in this same condition. In this case control

is seamlessly handed over from path follow to orientation

correction. Orientation correction acts quickly based only on

the robot’s current orientation in order to prevent it from

tipping or rolling over.

Most of the behaviours are self-explanatory, thus we only

present an hierarchical overview in Figure [7]. Additional

technical and implementation details can be found in our

open-source repository.

IV. Experiment results

Figures 1 and 8 contain photographs of the robot used
to test the methodology described in this paper. The system
was used in the DARPA SubT Urban event, some parts of the
Chillagoe-Mungana Caves, test facilities at CSIRO’s QCAT
site and various other locations.

Figure 8 shows sample costmaps as three different virtual
surfaces were approached. The photos were taken afterward
and do not represent the actual position of the robot in any
of the costmaps. The first two columns were recorded in the
Chillagoe-Mungana Caves. The third column was recorded
at CSIRO’s QCAT site.

[https://github.com/csiro-robotics][1] [will be available
soon.]
The first column depicts the robot approaching the edge of a rock cliff with a traversable slope next to it. The goal was set to a position beyond the bottom of the cliff. Initially the cliff is represented by a traversable virtual surface. Hybrid A* generated a path to drive off the cliff. As it approached the virtual surface became steeper until it was non-traversable. After this, the robot backed up and hybrid A* generated a path to avoid the steepest part of the cliff.

The second column shows the robot approaching a traversable downward slope. The original data that included the goal and hybrid A* paths was corrupted. The costmap was reproduced later based on raw data recorded from the sensors but the goal and paths were not. Initially the downward slope was virtual. During the approach the slope was observed and labelled as non-fatal.

The third column portrays the robot approaching the sharp edge of a platform. Again, hybrid A* initially planned off the edge. After getting close to the edge it was identified as non-traversable and the robot backed up and switched to a path that avoided it.

A. Performance evaluation

A robot may become damaged during a fall if it fails to avoid a negative obstacle. A Gazebo based simulation was used so that failures were acceptable. The simulation included analogues for most of the components in the system. Notably it included models of the vehicle, a Catpack and some environments. The vehicle model was geometrically accurate but made no attempt to emulate any dynamic mechanical components. The Catpack model had a tilted and rotating Velodyne that closely emulated a real Catpack. The accuracy of the geometry and sensor models made this simulation a useful tool during development and testing. The most significant inaccuracy of the simulation was in the environmental models. These were polygonal and did not emulate the natural complexity and roughness of real environments.

Figures 9 and 10 contain images of simulated tests of two alternative ways of handling virtual surfaces: treating them as traversable and treating them as non-traversable.

When virtual surfaces were considered traversable the non-traversable negative obstacle could not be handled. The third column of costmaps in Figure 9 illustrates this case. This is because the robot cannot possibly get any direct observations of the occluded vertical surface beyond the edge. The negative obstacle was always entirely virtual. Regardless of how close the robot got to the edge it could never directly observe the steepness of the negative obstacle below it. This resulted in the robot planning into the trench and falling.

When virtual surfaces were considered non-traversable the planner never attempted to move toward the obscured downward ramp. The second column of costmaps in Figure 10 illustrates this case. Reaching the goal required taking a detour down a ramp that could not be observed from the robot’s starting position. As the virtual surface above the ramp was considered non-traversable, the robot never found a path to the goal. The robot only ever planned to the closest position within the space before the ramp and never observed or attempted traversal of the ramp.

When virtual surfaces were considered the best case slope for whatever lies below, both cases could be handled. The first column of costmaps in Figures 9 and 10 illustrate these cases. In Figure 9 the robot approached the edge and identified the virtual surface as being representative of a non-traversable negative obstacle. In Figure 10 the robot planned onto the virtual surface above the ramp, moved toward the ramp, observed the ramp, then planned down the ramp and to the goal.
down the slope. To better handle the approach, firstly the robot must get close to the downward toward the negative obstacle. Without handling this inevitably leads to the robot falling off the top of a sphere. In many cases during testing, the robot ended up on a slope that it could not traverse without sliding. This approach procedure is dangerous, especially for slopes that get steeper slowly such as driving on a platform over a large body of water, beams aimed at the water may be reflected or refracted away from the sensor by the glassy surface of the water. The OHM map could generate virtual surfaces for these regions if information about the non-returning beams becomes available. This approach would adequately handle the scenario and the costmap could label the resulting virtual surfaces as non-traversable.

There is a significant delay (seconds) between the time when the robot is in a position capable of determining if a negative obstacle is fatal or not and the time when a costmap that includes that information is published. Currently, this delay is not considered, so the robot is at a significant risk of driving off the edge of a negative obstacle before it gets a chance to realise it is fatal. Firstly, this delay should be minimised in order to allow the robot to quickly determine fatality and move on. Secondly, this delay must be adequately be handled in order to prevent driving onto virtual surfaces.

A downward slope is considered a negative obstacle when it is too steep to safely traverse. In order to determine if the slope is too steep, the robot must get close to the downward slope, it must get close to the region that it may not be able to safely traverse. This approach procedure is dangerous, especially for slopes that get steeper slowly such as driving off the top of a sphere. In many cases during testing, the robot ended up on a slope that it could not traverse without sliding downward toward the negative obstacle. Without handling the sliding correctly this inevitably leads to the robot falling down the slope. To better handle the approach, firstly the robot should move in line with the gradient of the slope so that it can back out safely without sliding and secondly it should stop when it is close enough to determine if it is too steep and wait for new observations to be made and processed.

V. DISCUSSIONS AND LIMITATIONS

A. Virtual surfaces

Limitations in the lidar driver make it impossible to accurately identify lidar samplings which do not yield a valid return within the sensor range. This is in part due to the ambiguity between returns which are beyond the sensor range and returns which lie within the sensor minimum range and in part due to the difficulty in determining the direction of the beam.

The lack of this information means that observations can only be made where valid returns are generated. Virtual surfaces can only be generated by such observations. Information may be missing from the map where no returns are generated. For example, if the robot approaches the edge of a platform over a large body of water, beams aimed at the water may be reflected or refracted away from the sensor by the glassy surface of the water. The OHM map could generate virtual surfaces for these regions if information about the non-returning beams becomes available. This approach would adequately handle the scenario and the costmap could label the resulting virtual surfaces as non-traversable.

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B. Planning

The method used to label fatal obstacles in the costmap (see Section III-C) is susceptible to incorrectly labelling the ends of thin but deep trenches as non-traversable where the robot can easily and safely traverse (see Figure 11). In addition, as only one method was used, it was tuned to handle both continuous slopes and discrete steps despite these two cases being represented significantly differently in the heightmap. To address this, one method should be used to detect non-traversable discrete steps and a different, independent method should be used to detect non-traversable continuous slopes. The method that was used in this work should not be used for either purpose.

The cost functions used in the costmap and in the planner both considered the robot to be a rigid rectangle capable of full control at all times. This lead to two problems. Firstly, the planner planned to traverse small obstacles that were taller than the vehicle’s clearance but thinner than the gap between the vehicle’s tracks. This often caused the vehicle to get stuck on top of such obstacles. Secondly, the planner assumes the vehicle can turn using full traction on both tracks at all times. When the vehicle is laterally traversing a slope (such that it is slightly rolled) the downhill track is supporting more weight than the uphill track. The downhill track has greater traction. Turning is not reliable when the left and right track have different amounts of traction. The planner should apply a penalty to making use of the uphill track when on a slope.

Finally, the requirement to explore into unknown and possibly non-traversable areas means that the planner must be able to return partial paths which do not reach the goal it was given but get as close as possible. This poses significant risk near negative obstacles as it can mean driving the robot into the most unsafe possible non-fatal position. Improvements in candidate path selection when no complete path is possible could allow the robot to move into equivalent but significantly safer positions.
VI. CONCLUSIONS

In this paper we have demonstrated a simple yet efficient technique for generating a best case surface prediction in regions of poor sensor observation. These predictions have been named virtual surfaces and can be effectively costed in path planning to generate valid paths which first approach, then avoid such poorly observed regions. We have also demonstrated how negative obstacles can be inferred by the presence of virtual surfaces and how these surfaces change on approach. Practical testing has built confidence that this approach is capable of handling a variety of difficult terrain.

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