

# Spatio-Temporal Semantic Occupancy Grids: A Continuous-Time Probabilistic Approach for High-Dynamic Environments

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**Abstract**—Traditional Simultaneous Localization and Mapping (SLAM) approaches typically rely on the “static world assumption,” treating the environment as a binary state of occupied or free. This approach fails in high-dynamic environments where obstacles (e.g., chairs, people) are transient. This paper proposes a novel Temporal Probabilistic Costmap that utilizes continuous-time integration and semantic-based entropy. By assigning dynamic “memory horizons” based on object classification and implementing a “drift-to-mean” probability function, we demonstrate a navigation framework that inherently understands the stability of its environment. We further propose a hierarchical partitioning architecture to manage these high-resolution temporal histories on resource-constrained mobile robots.

**Index Terms**—Semantic Navigation, Probabilistic Mapping, ROS 2, Dynamic Environments, Costmap Layers.

## I. INTRODUCTION

Standard Robot Operating System (ROS) navigation stacks utilizing occupancy grids (e.g., `nav2_costmap_2d`) operate on a “latest observation” bias. If a sensor clears a voxel, it is marked free; if it hits a voxel, it is marked occupied. This binary toggling creates “jittery” global planning in dynamic spaces, such as cafeterias or busy hallways.

We argue that **Occupancy is not a state, but a probability over time**. A hallway is not “blocked”; it is “currently blocked with low confidence of persistence.” Conversely, a couch is not just “occupied”; it is “structurally occupied with high confidence.”

## II. METHODOLOGY

### A. Continuous-Time Integration

To address the irregularity of sensor observations, we reject discrete event counting in favor of continuous time weighting. We define the cost of a cell not by the number of hits, but by the duration of the state, weighted by its recency.

Let  $H$  be the set of observation intervals for a specific grid cell. The raw probability  $P_{raw}$  is calculated by integrating the state duration  $d$  against a linear decay function  $W(t)$ :

$$P_{raw} = \frac{\sum_{i=0}^N (S_i \cdot d_i \cdot W(t_i))}{\sum_{i=0}^N (d_i \cdot W(t_i))} \quad (1)$$

Where  $S_i \in \{0, 1\}$  represents the observed state. This ensures that a stable observation of 100ms carries more weight than a sensor noise burst of 5ms, regardless of sampling rate.

### B. The “Drift-to-Mean” Entropy Model

We introduce the concept of **Information Entropy** relative to time. As the time since the last observation ( $t_{age}$ ) increases, the system’s confidence  $C(t)$  decreases. Rather than defaulting to “Free” (0.0) or “Occupied” (1.0), the system drifts toward maximum entropy (0.5).

The effective probability  $P_{eff}$  is defined as:

$$P_{eff} = (P_{obs} \cdot C(t)) + (0.5 \cdot (1 - C(t))) \quad (2)$$

Where  $C(t)$  is a linear function of the memory horizon  $T_{horizon}$ :

$$C(t) = \max \left( 0, 1 - \frac{t_{age}}{T_{horizon}} \right) \quad (3)$$

This creates a “Fog of War” where unobserved areas gradually fade to a cost of 127 (Grey), discouraging the planner from assuming safety in unmonitored regions.

### C. Semantic Memory Horizons

A critical innovation of this framework is the **Dynamic Horizon**. We reject a global decay rate. Instead,  $T_{horizon}$  is determined by the semantic class of the object occupying the cell, provided by an upstream vision system (e.g., YOLO/SSD).

TABLE I  
SEMANTIC DECAY HORIZONS

Object Class	Mobility	Horizon ( $T_{horizon}$ )	Rationale
Structure (Wall)	0.0	$\infty$	Permanent
Heavy (Couch)	0.1	4 Hours	High Friction
Light (Chair)	0.5	5 Minutes	Frequently Moved
Agent (Person)	1.0	5 Seconds	Transient

This allows the costmap to “remember” a couch for hours while “forgetting” a walking person in seconds.

### III. ALGORITHM

The core logic for the cost calculation of a single cell is described in Algorithm 1.

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**Algorithm 1** Temporal Semantic Cost Calculation

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0: Input: History  $H$ , CurrentTime  $T_{now}$ , SemanticClass  $Obj$ 
0: Output: Cost  $C_{final} \in [0, 254]$ 
0:  $T_{horizon} \leftarrow \text{LOOKUPHORIZON}(Obj)$ 
0:  $P_{baseline} \leftarrow 0.5$ 
0:  $Area_{weighted} \leftarrow 0$ 
0:  $Duration_{total} \leftarrow 0$ 
0: for each observation  $obs_i$  in  $H$  do
0:    $t_{start} \leftarrow obs_i.time$ 
0:    $t_{end} \leftarrow \min(obs_{i+1}.time, T_{now})$ 
0:    $d \leftarrow t_{end} - t_{start}$ 
0:    $t_{age} \leftarrow T_{now} - (t_{start} + d/2)$ 
0:   Comment: Calculate Confidence
0:    $conf \leftarrow \max(0, 1 - (t_{age}/T_{horizon}))$ 
0:   Comment: Apply Drift-to-Mean
0:    $p_{raw} \leftarrow (obs_i.is\_occupied)?1.0 : 0.0$ 
0:    $p_{eff} \leftarrow (p_{raw} \cdot conf) + (P_{baseline} \cdot (1 - conf))$ 
0:    $Area_{weighted} \leftarrow Area_{weighted} + (p_{eff} \cdot d)$ 
0:    $Duration_{total} \leftarrow Duration_{total} + d$ 
0: end for
0:  $P_{final} \leftarrow Area_{weighted}/Duration_{total}$ 
0: return  $P_{final} \times 254$ 

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### IV. SYSTEM ARCHITECTURE

To adhere to hardware constraints (e.g., 8GB RAM), we implement a **Two-Tier Spatial Hierarchy**:

- **Macro-Layer (Topological):** The environment is partitioned into semantic regions (e.g., Rooms of  $50 \times 50$  ft). Each node contains an aggregate “Busyness Score.”
- **Micro-Layer (Temporal Grid):** Detailed temporal history buffers are loaded into RAM only for the active region and its neighbors. Dormant regions are serialized to disk.

### V. CONCLUSION

By shifting the paradigm from binary occupancy to probabilistic semantic persistence, we enable mobile robots to navigate high-dynamic environments with human-like intuition. The robot avoids areas it “knows” are busy, treats unobserved areas with caution, and respects the permanence of heavy infrastructure while ignoring transient noise.