# **Engineering A\* for Autonomous Path Planning of Tracked Vehicle**

### **Project Guide**

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# INTRODUCTION

### **Project Scope:**

Optimizing path planning approaches for autonomous tracked tanker vehicle movement across multiple terrains.

### **Objectives:**

- Understand and identify permafrost zones in terrain of strategic importance.
- Avoidance of hazardous or thaw-prone areas in vehicle path planning.
- Implement terrain-aware A\* for mission-critical autonomous navigation in the Himalayas.

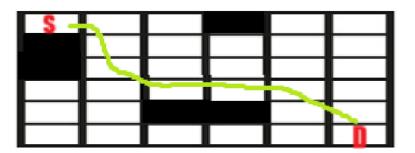
### Why A\* Algorithm?

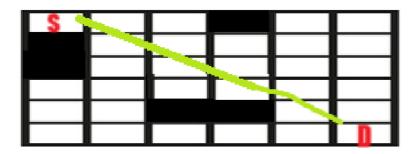
- ❖ A widely used graph-based search algorithm in path planning.
- \* Requires optimization for real-world constraints like terrain elevation, environmental factors, and GIS data integration.

# **CHALLENGES**

### **Key Challenges:**

**1. Path Planning Issues in GIS-based Systems -** A\* struggles with real-world elevation variations, obstacles, and various terrain constraints. The main issue faced is as shown in the figure below:





Observed planning Required planning

# **CHALLENGES**

### **Key Challenges:**

- **2. Developing a Permafrost Map -** Autonomous navigation in cold regions requires understanding permafrost risks that are to be avoided. Key risks include:
  - **Unstable Ground Conditions** Risk of sinking or immobilization
  - **Thermokarst Formation** Depressions and cracks in terrain
  - Surface Strength Variability Sudden loss of ground support
  - **Ice Accumulation & Slippage** Reduced traction and control
  - Cold-Induced Failures Mechanical and electronic malfunctions
  - **Vehicle Heat Impact** Local permafrost thawing risk
  - **Sensor Reliability Issues** Obstructed LiDAR and cameras
  - Waterlogged Terrain High resistance and energy usage
  - Path Planning Challenges Constant terrain changes

### **Region of Interest & Time Period (INDIA):**

- **Coordinates:** 75.5°E to 80.5°E, 36.5°N to 28.5°N
- **Key Locations in India:** Leh, Kargil, Diskit, Hunder, Turtuk, Panamik, Sumur, Alchi, Likir, Basgo, Nimoo, Lamayuru, Saspol, Uleytokpo, Rizong
- Extended Plains: Chandigarh, Ambala, Ludhiana, Patiala, Amritsar, Shimla, Solan, Dehradun, Meerut, Saharanpur, etc.
- Time Period: January 2020 to December 2023

### **Permafrost Probability Model**

- Derived a weighted equation from literature (Raza et al., Overduin et al.)
- Formula: X = Wm \* Rm + Wp \* Rp + Wa \* Ra + Ws \* Rs; PE = X \* GSC
- Input factors:
  - MAAT (BMAT from MODIS LST)
  - Slope & Aspect (from SRTM DEM)
  - PISR (Potential Solar Radiation)
  - Ground Surface Cover (NDVI, NDSI)
- Normalized ratings and fixed weights (Wm=0.4, Wp=0.2, Wa=0.2, Ws=0.2) 09-05-2025 CAIR, DRDO

#### Weights:

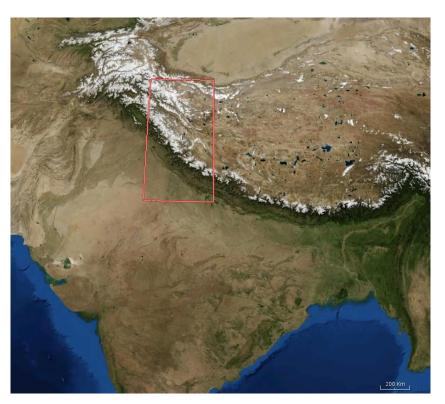
- **W**<sub>m</sub> Weight for MAAT / BMAT (here, 0.4)
- W<sub>n</sub> Weight for PISR (0.2)
- W<sub>a</sub> Weight for Aspect (0.2)
- W<sub>s</sub> Weight for Slope (0.2)

#### Ratings (normalized indices or reclassified scores):

- R<sub>m</sub> Rating based on MAAT (from MODIS LST)
- R<sub>p</sub> Rating based on PISR (from solar radiation models)
- Ra Rating based on aspect (north-facing vs. south-facing)
- R<sub>s</sub> Rating based on slope steepness

**Ground Surface Cover Factor: GSC** – Ground Surface Cover coefficient (derived from NDVI, NDSI, land cover classification). It adjusts the combined score to reflect the insulating or exposing effect of vegetation/snow/rock types.

**PE: Permafrost Estimation (PE)** – Final probabilistic score indicating presence/absence likelihood of permafrost.



### **Step-by-Step Functionality:**

### 1. Load Input Data

- Reads raster files: DEM, LST, NDVI, Slope, NDSI, Soil properties, FDD, and TDD.
- Resamples them to a common spatial resolution and shape using the DEM as reference.

#### 2. Clean FDD and TDD

- Ensures all invalid values (NaN, inf, negative) are handled.
- Resizes if shapes don't match.

### 3. Estimate Soil Thermal Properties

- Computes frozen (Kf) and thawed (Kt) thermal conductivity using clay and bulk density.
- Clips them to realistic physical ranges.

#### 4. Estimate n-factors

- Surface energy balance correction using NDVI and NDSI:
  - o nf for freezing
  - o nt for thawing

**5. Compute TTOP (Temperature at the Top of Permafrost):** Where MAAT is approximated from LST.

$$ext{TTOP} = ext{MAAT} imes n_f - n_t imes \left(rac{K_t}{K_f}
ight)$$

### 6. Compute ALT (Active Layer Thickness)

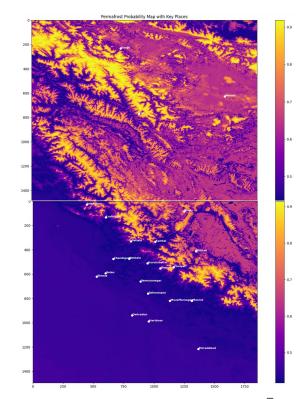
$$ext{ALT} = \sqrt{rac{2 \cdot k \cdot ext{FDD}}{L_f \cdot 
ho}}$$

#### Where:

- k = average thermal conductivity
- Lf = latent heat of fusion of water
- $\rho$  = soil density
- **7. Classify High Confidence Permafrost Zones:** Zones where ALT < 1.5 m are marked as permafrost.
- 8. Compute Final Permafrost Probability:

$$Probability = \frac{Normalized\ TTOP + Normalized\ MAGT + (1-ALT/5)}{3}$$

- 9. Export Outputs
  - ALT.tif: Estimated active layer thickness
  - Permafrost\_Probability.tif: Final combined permafrost probability map
  - PermafrostZone\_ALT\_lt\_1\_5.tif: Binary mask of high-confidence permafrost



#### **References:**

#### 1. TTOP (Temperature at the Top of Permafrost) Equation

- Smith and Riseborough (2002). "Climate and the limits of permafrost: a zonal analysis." Permafrost and Periglacial Processes.
- This equation relates Mean Annual Air Temperature (MAAT), soil thermal conductivities, and n-factors to estimate the ttop.

#### 2. Active Layer Thickness (ALT) Equation

- Lunardini (1981). "Heat Transfer in Cold Climates."
- This is based on the Stefan equation, which estimates the depth of seasonal thaw in frozen ground using:
  - o Thermal conductivity k
  - o Freeze Degree Days (FDD)
  - o Soil density ρ
  - Latent heat of fusion L f

#### 3. Thermal Conductivity Estimation (Kf, Kt)

- Modified from empirical formulations by Zhang et al. (2008) and Riseborough et al. (2008)
- These equations approximate frozen and thawed soil conductivity using bulk density and clay content, which are key factors influencing soil thermal behavior.

#### 4. n-Factor Estimation

nf = np.where(NDVI > 0.2, 0.7, 0.5) nt = np.where(NDSI > 0.3, 0.6, 0.9)

- Klene et al. (2001); Zhang et al. (1997)
- Empirical assignment of freezing (nf) and thawing (nt) n-factors based on vegetation (NDVI) and snow (NDSI). These affect the surface energy balance.

#### 5. MAGT Proxy Equation

#### Coefficients used:

$$\alpha = -1.5$$
,  $\beta = -2.2$ ,  $\delta = -0.5$ ,  $\epsilon = -0.2$ ,  $C = 5.0$ 

- Derived from methods in:
  - O Obu et al. (2019), Northern Hemisphere permafrost map
  - o Kumar et al. (2021), Permafrost modeling in the Indian Himalayas
- This equation combines normalized environmental variables to approximate MAGT where borehole data is unavailable.

#### 6. Permafrost Probability

- Composite logic adapted from Obu et al. (2019) and Raza Khan et al. (2021) for probability mapping.
- It integrates thermal (TTOP, MAGT) and physical (ALT) indicators for robust classifications

$$ext{TTOP} = ext{MAAT} imes n_f - n_t imes \left(rac{K_t}{K_f}
ight)$$

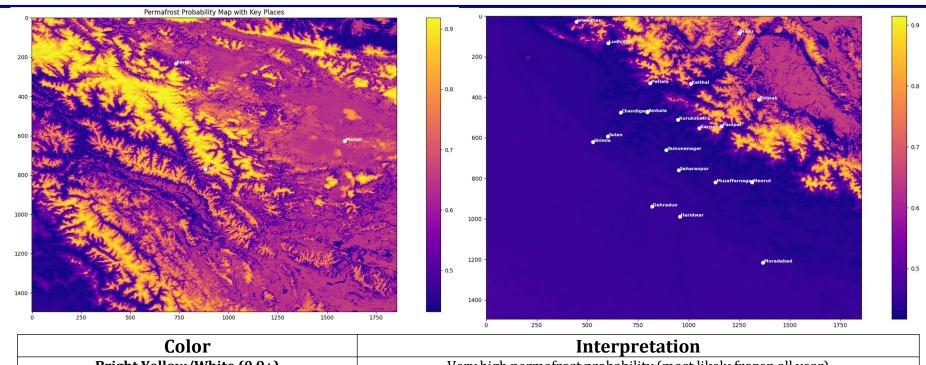
$$ext{ALT} = \sqrt{rac{2 \cdot k \cdot ext{FDD}}{L_f \cdot 
ho}}$$

$$K_f = 1.5 + 0.5 \cdot \left(rac{ ext{bulk density}}{1.6}
ight) + 0.01 \cdot ext{clay}$$

$$K_t = 0.5 + 0.3 \cdot \left(rac{ ext{bulk density}}{1.6}
ight) + 0.005 \cdot ext{clay}$$

$$\begin{aligned} \text{MAGT} &= \alpha \cdot \text{LST} + \beta \cdot \text{NDVI} + \delta \cdot \text{slope} \\ &+ \epsilon \cdot \text{elevation} + C \end{aligned}$$

$$Probability = \frac{Normalized\ TTOP + Normalized\ MAGT + (1 - ALT/5)}{1 - ALT/5}$$



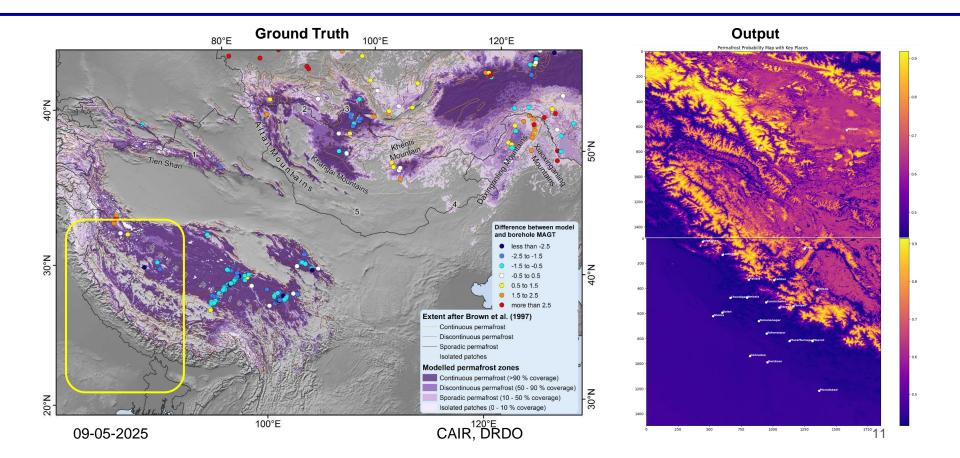
Color	Interpretation		
Bright Yellow/White (0.9+)	Very high permafrost probability (most likely frozen all year)		
Orange to Purple (~0.6 - 0.8)	Moderate to high likelihood – likely continuous or discontinuous permafrost		
Dark Purple (< 0.5)	Low or no permafrost – could be seasonally thawing or warm terrain		

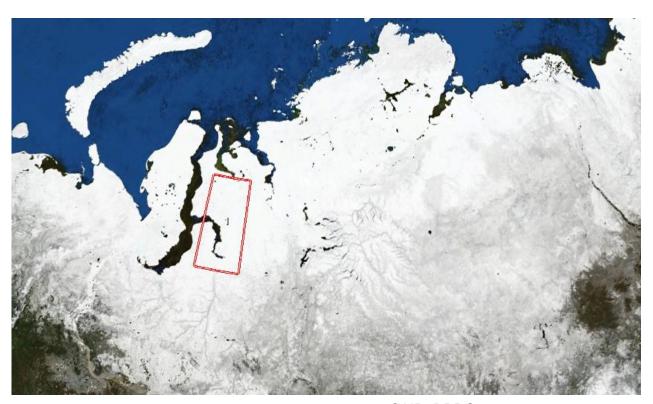
#### Observation:

- Most terrain around Leh and Kargil is bright yellow, meaning high permafrost potential.
- Manali region shows relatively lower intensity (orange-purple), indicating transitional or patchy permafrost.

```
--- Input Checks for ALT Calculation ---
FDD: min= 0.0 max= 5000.0 mean= 4629.1035
rho: min= 0.0 max= 144947.64 mean= 111725.0
k: min= 1.0 max= 2.0 mean= 1.9099519
ALT stats — min: 0.0 max: 1.3941911617060292 mean: 0.000636300368129048
Permafrost pixel count (ALT < 1.5m): 277215314
```

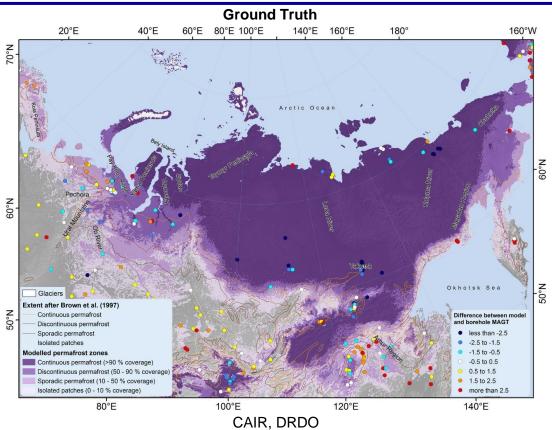
Parameter	Explanation	Meaning				
FDD	Freeze Degree Days	Min = 0.0, Max = 5000.0, Mean = 4629.1 → shows the total freezing thermal load over the year. A high mean suggests long and cold winters, suitable for permafrost formation.				
rho	Soil density (kg/m³)	Mean = 111725 → This seems 100x higher than typical (~1300–1600 kg/m³), likely because bulk_density was already in kg/m³ but was multiplied again. This high density artificially reduces ALT thickness.				
k	Thermal conductivity (W/mK)  Range is realistic: 1.0–2.0 W/mK - indicates moderate to high conductivity depending on soil type.					
ALT stats	Active Layer Thickness (m)	Max = 1.39 m, Mean = $0.0006$ m $\rightarrow$ The extremely low mean means most regions are predicted to be <b>near-frozen year-round</b> , i.e., likely permafrost.				
Permafrost pixel count	Number of pixels where ALT < 1.5 m	$277,215,314 \rightarrow \text{Almost all pixels in your}$ study area are considered permafrost under this condition.				

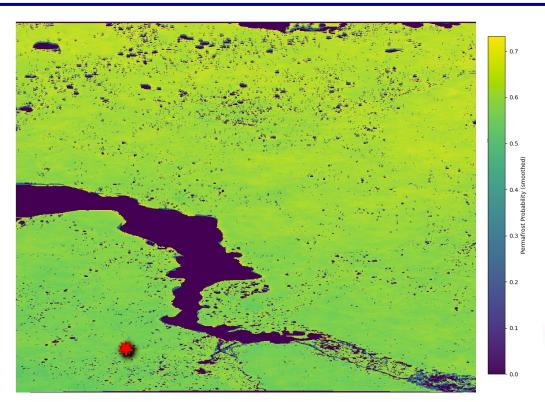




# Region of Interest & Time Period (RUSSIA):

- **Coordinates:** 75.5°E to 80.5°E, 67.0°N to 71.0°N
- Key Locations in India: Salekhard, Labytnangi, Nadym, Novy Urengoy, Noyabrsk, Tazovsky, Antipayuta, Gyda, Yamburg, Sabetta
- Time Period: January 2020 to December 2023



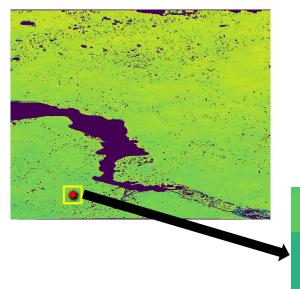


### Output:

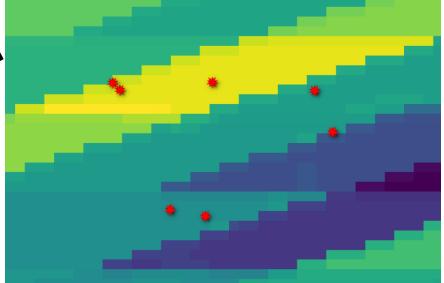
--- Input Checks for ALT Calculation --FDD: min= 0.0 max= 5000.0 mean=
4556.725
rho: min= 0.0 max= 139894.02 mean=
105376.97
k: min= 1.0 max= 2.0 mean=
1.8855983
ALT stats — min: 0.0 max:
2.54236106189146 mean:
0.0006644549458326142
Permafrost pixel count (ALT < 1.5m):
276547365



**Borehole Data Available** 

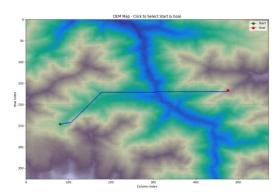


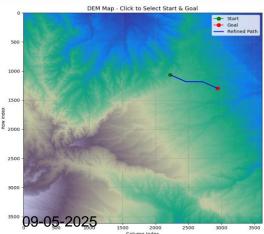
Borehole_ID	Longitude	Latitude	MAGT_C	MAGT_De	Year_Drill	PF_Thickness
RU 05 03_0001	76.68969	67.47813	-0.9	9	2006	>100
RU 37 03_0039	76.68989	67.47793	-3.1	9	2008	>100
RU 33 03_0035	76.69128	67.47461	-3.8	10	2008	>100
RU32 03_0033	76.69226	67.47443	0.1	8	2006	NPF
RU 36 03_0038	76.69245	67.47814	-3.7	10	2008	>100
RU 35 03_0037	76.69529	67.47791	-3.8	10	2007	>100
RU 34 03_0036	76.69579	67.47676	-0.8	8	2008	>100



# **A\* PROBLEM MANIFESTATION**

### Simple A\* over DEM without any Constraints





### **Reasons:**

#### **Raster Grid Constraints**

- The DEM is a discrete grid, not a continuous surface.
- A\* must move from pixel to pixel either horizontally, vertically, or diagonally.
- So even the "straightest" diagonal will be an approximation (like a stair-step pattern).

#### 8-Connected Grid Search

- The directions allowed are limited to:
  - o 4 cardinal (N, S, E, W)
  - o 4 diagonal (NE, NW, SE, SW)
- There's no interpolation between directions, so the path is forced to switch between these options to approximate diagonality.

#### **Uniform Cost:**

- All open cells = same cost.
- Path can't distinguish truly free space from edges, causing detours.

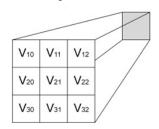
### **Binary Slope Filter:**

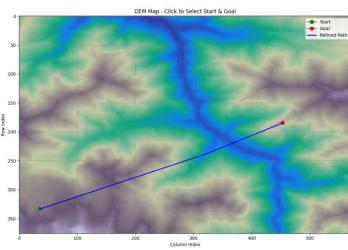
- Slope is pass/fail, no extra penalty for steep areas.
- Encourages hugging if edges remain just under slope cutoff.

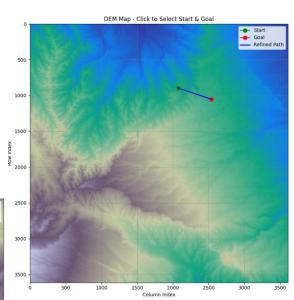
CAIR, DRDO

### Simple A\* with Pixel Resampling over DEM without any Constraints

# A Star with Grid Resampling (Creates Sub pixels inside each pixel)







```
substeps = 4
directions = [(dx / substeps, dy / substeps)
for dx in range(-substeps, substeps + 1)
for dy in range(-substeps, substeps + 1)
if not (dx == 0 and dy == 0)]
```

It considers movements like  $\pm 0.25$ ,  $\pm 0.5$ , ... up to  $\pm 1$  in all 8 directions.

def heuristic(a, b):
 return np.hypot(a[0] - b[0], a[1] - b[1])

Euclidean distance between two points, used as the heuristic estimate.

tentative\_g = g\_score[current] + np.hypot(dx, dy)
 if neighbor not in g\_score or tentative\_g <
g\_score[neighbor]:</pre>

came\_from[neighbor] = current
g\_score[neighbor] = tentative\_g
f\_score = tentative\_g + heuristic(neighbor,
goal)

heapq.heappush(open\_set, (f\_score, neighbor))

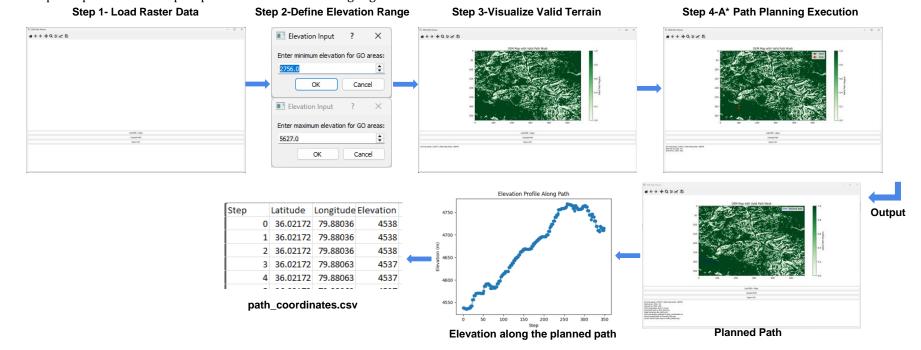
• tentative\_g: cost from start to this neighbor via current.

If this path is better than previously known, update:

- came\_from: record that current led to neighbor.
- g\_score: store updated cost.
- Compute f\_score and add neighbor to open\_set

### **DEM-Based Path Planning GUI Using Elevation and Slope-Constrained Subpixel A\* Search**

This GUI-based application performs elevation-aware path planning using A\* algorithm over a Digital Elevation Model (DEM) and slope raster input. The DEM provides elevation values, while slope is used to eliminate unsafe traversal areas (> 35°). User inputs the minimum and maximum elevation values to define the GO (go-operable) area. The system creates a binary mask where pixels are marked valid if elevation and slope conditions are met. The GO area is rendered on the map. Users can click to select start and goal points only within valid terrain. The GUI runs a subpixel A\* algorithm (32-directional search, 4 substeps) over the valid mask. The computed path avoids steep slopes and elevation-violating regions.



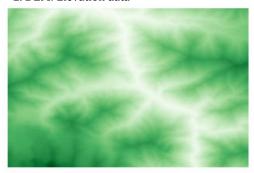
**DEM-Based Path Planning GUI Using Elevation and Slope-Constrained Subpixel A\* Search** 

### 1. Data Inputs

#### **DEM and Slope Raster Input:**

The GUI accepts two GeoTIFF inputs:

1. DEM: Elevation data



2.Slope Raster: Precomputed terrain slope

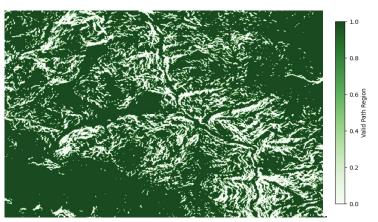


### **Cost Map Generation**

#### GO Area and Valid Mask:

Based on user-defined elevation bounds [min,max][min, max][min,max], two binary masks are created:

self.go\_area = (self.dem\_data >= self.min\_elev) & (self.dem\_data <= self.max\_elev)
self.valid\_mask = self.go\_area & (self.slope\_data <= 45)</pre>



Pixels outside the elevation range or with slope >  $45^{\circ}$  are marked invalid. Final mask valid\_mask is used for path expansion (1.0 = valid, 0.0 = blocked).

**Green to dark green (1.0)** = Navigable **White (0.0)** = Non-navigable CAIR, DRDO

**DEM-Based Path Planning GUI Using Elevation and Slope-Constrained Subpixel A\* Search** 

### **A\* Pathfinding Logic**

### A\* Pathfinding Logic with Subpixel Precision

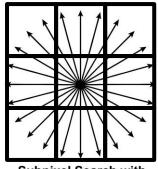
#### 1. Start & Goal Selection:

User selects start and goal interactively on valid terrain using mouse clicks.

### 2. Subpixel Search with 32 Directions:

The A\* algorithm is extended to support subpixel resolution and smooth path transitions by using 32 angular directions:

```
directions = [
    (np.cos(theta), np.sin(theta))
    for theta in np.linspace(0, 2 * np.pi, 32, endpoint=False)
]
```



Subpixel Search with 32 Directions

### A\* Core Loop

```
for dx, dy in directions:
    neighbor = (current[0] + dx / substeps, current[1] + dy / substeps)
    r, c = int(neighbor[0]), int(neighbor[1])
    if 0 <= r < rows and 0 <= c < cols and self.valid_mask[r, c]:
        tentative_g = g_score[key] + np.hypot(dx, dy) / substeps
        f_score = tentative_g + heuristic(neighbor, goal)
        heapq.heappush(open_set, (f_score, neighbor))</pre>
```

For each direction, take a small step (dx/substeps, dy/substeps). If this step doesn't get us closer to the goal, skip it (gradient descent behavior).

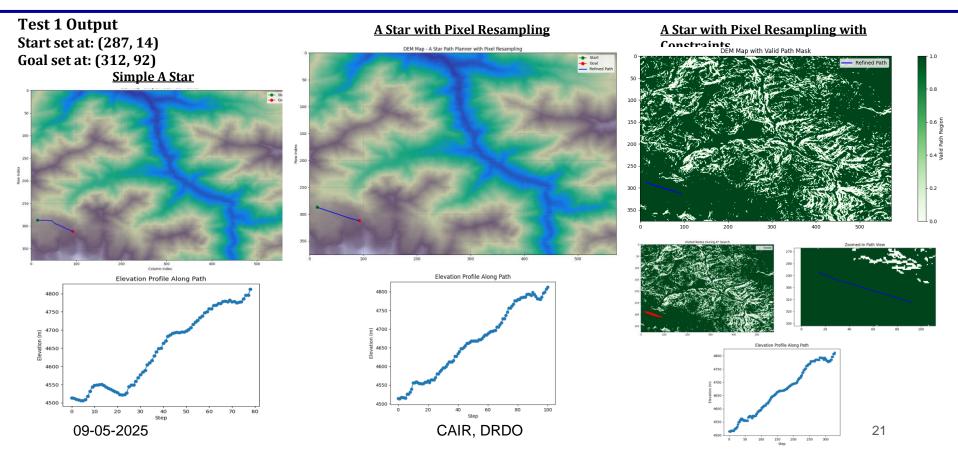
Converts floating-point neighbor to pixel indices.

Only accept points within map bounds and marked as valid in self.valid\_mask

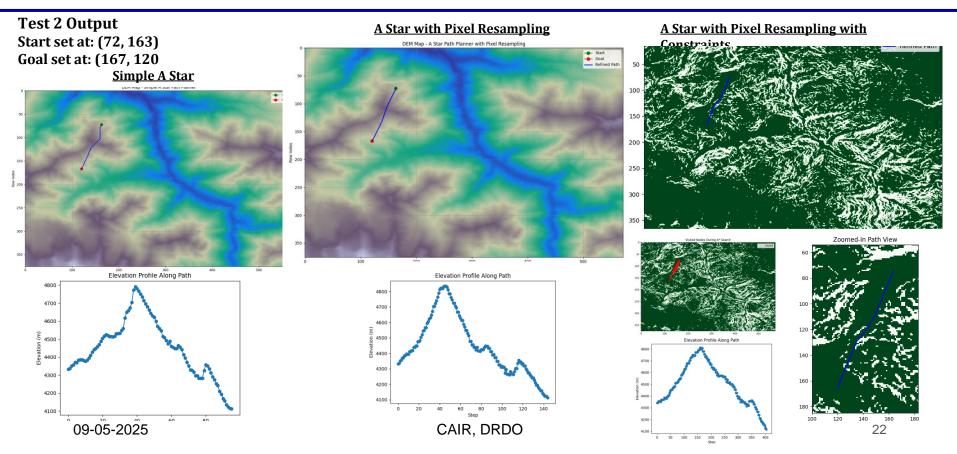
**g-score**: Cumulative travel cost (Euclidean distance between steps)

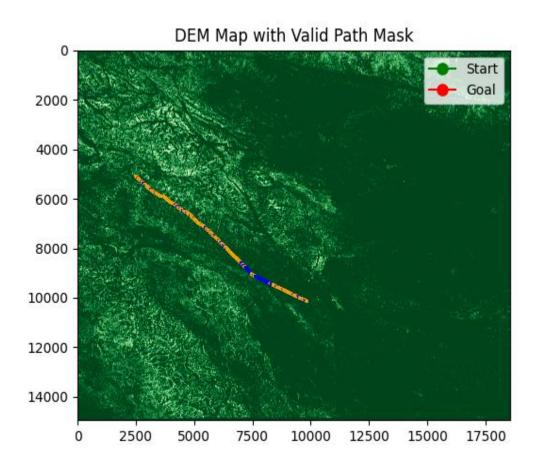
Heuristic: Euclidean distance between two floating-points

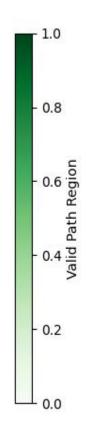
**DEM-Based Path Planning GUI Using Elevation and Slope-Constrained Subpixel A\* Search** 

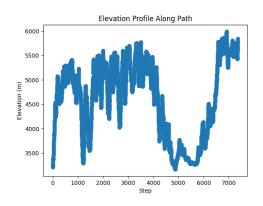


**DEM-Based Path Planning GUI Using Elevation and Slope-Constrained Subpixel A\* Search** 









- Blue for low-slope segments (≤ 15°)
- Orange for moderate slope (15° to 45°)
- Red for higher slopes (if allowed)

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