Department of War HBCU/MI Summer Research Internship Program

Automated Road Network Characterization for Enhanced Chokepoint Analysis

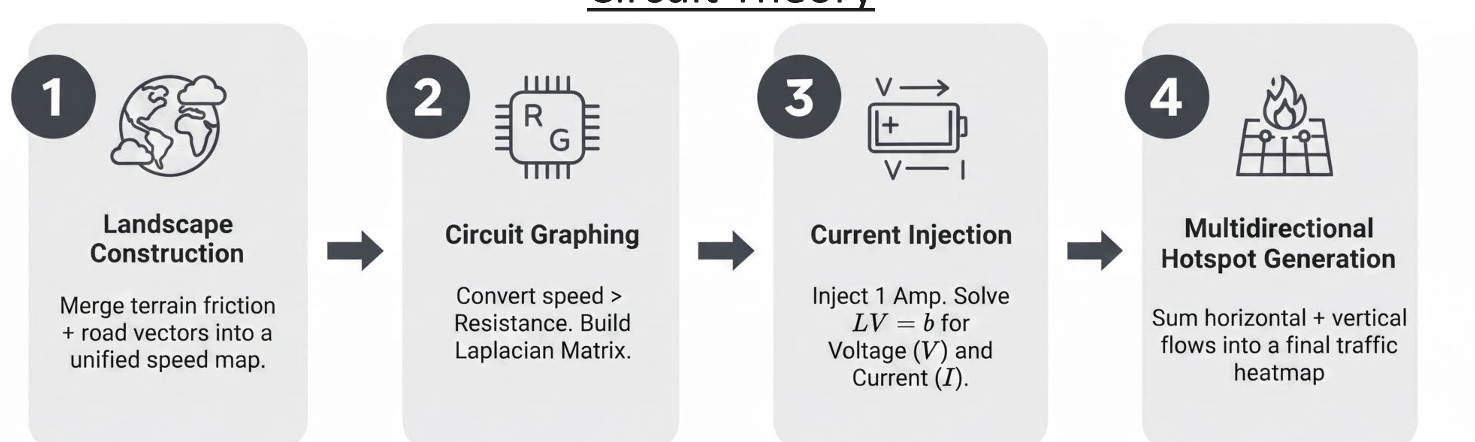
Fernando Sepulveda, ERDC/ GRL, fasepulveda@miners.utep.edu

Introduction/ Background

In mission planning, the rapid and accurate identification of chokepoints—such as narrow passages, bridges, and complex intersections—is critical for logistics, mobility, and force protection.

- **The Bottleneck:** Currently, characterizing road geometry (e.g., calculating turning angles) and identifying chokepoints is a manual, labor-intensive process for DoD personnel.
- **The Risk:** Manual analysis slows down tactical decision-making and limits the scale of geospatial intelligence that can be processed in dynamic environments.
- **The Mission Need:** The U.S. Army Engineer Research and Development Center (ERDC) requires automated, highly accurate capabilities to rapidly process road network datasets.

Circuit Theory



Methodology

Method	Inputs	Pipeline	Outputs/ Advantages
1. Circuit Extraction	Circuit Flow Raster	Normalizes flow to 8-bit scale → 95th percentile thresholding → cv2.findContours.	Extracts highest density traffic flows & labels polygons
2. Fusion of Algorithms & CV Validation	Flow Raster + RGB Satellite Imagery	Uses Polygon from M#1 and applies Canny Edge Detection	Overlays hotspots and scores traversability
3. Pure CV	RGB Satellite Imagery	Utilizes (.cdist) to measure/ flag obstacles (15-300 pixels are categorized as bottlenecks)	Ignores Circuit Math, Identifies Obstacles and Bottlenecks
4. Semantic CV Approach	RGB Satellite Imagery	Utilizes K-Means Clustering instead of using just “edges” to identify land types	Outputs a pure CV bottleneck labeled land with Semantics
5. Deep Learning CV Approach	RGB Satellite Imagery	Passes tensor to Ultralytics' FastSAM-s	Leverages ZeroShot AI to segment new maps & Identify chokepoints

Results

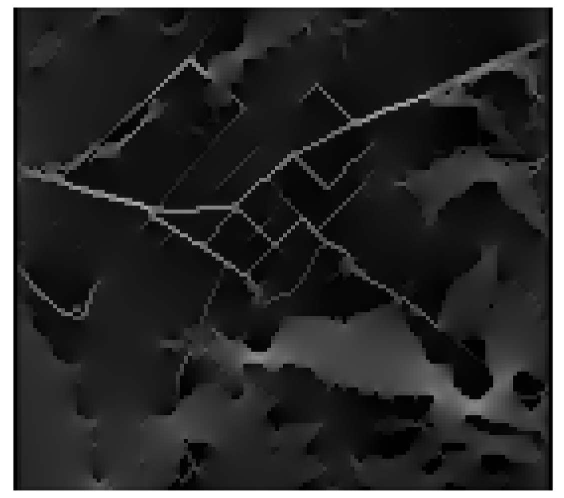


Image 1: Circuit Flow Raster of Single Direction CT

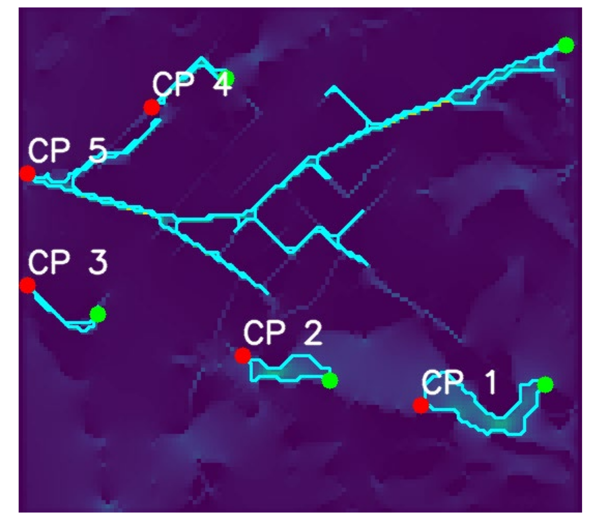


Image 3: Method #1 with Single Direction CT


Image 5: Method #2 with Single Direction CT

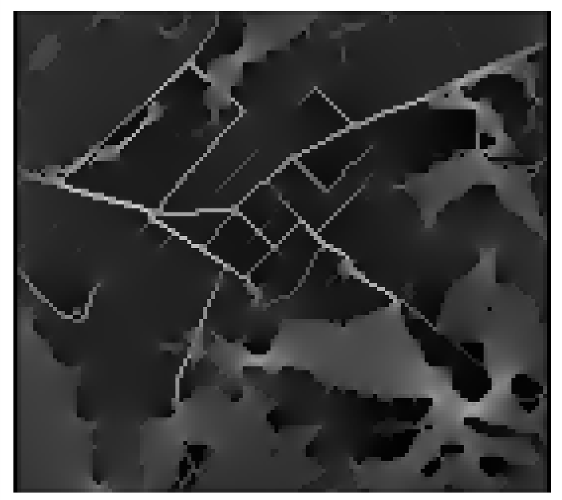


Image 2: Circuit Flow Raster of Multi Direction CT

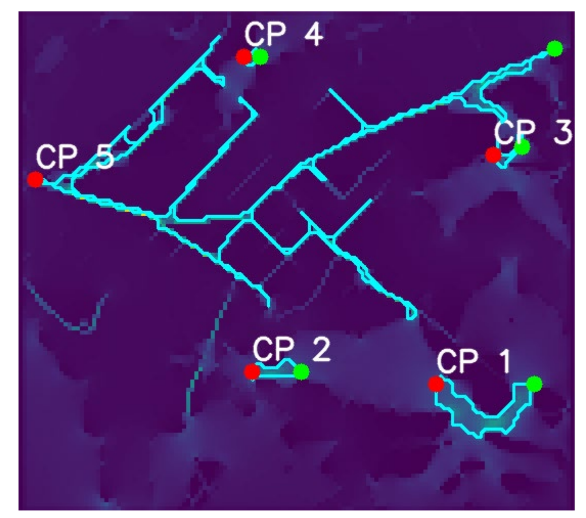


Image 4: Method #1 with Multi Direction CT


Image 6: Method #2 with Multi Direction CT

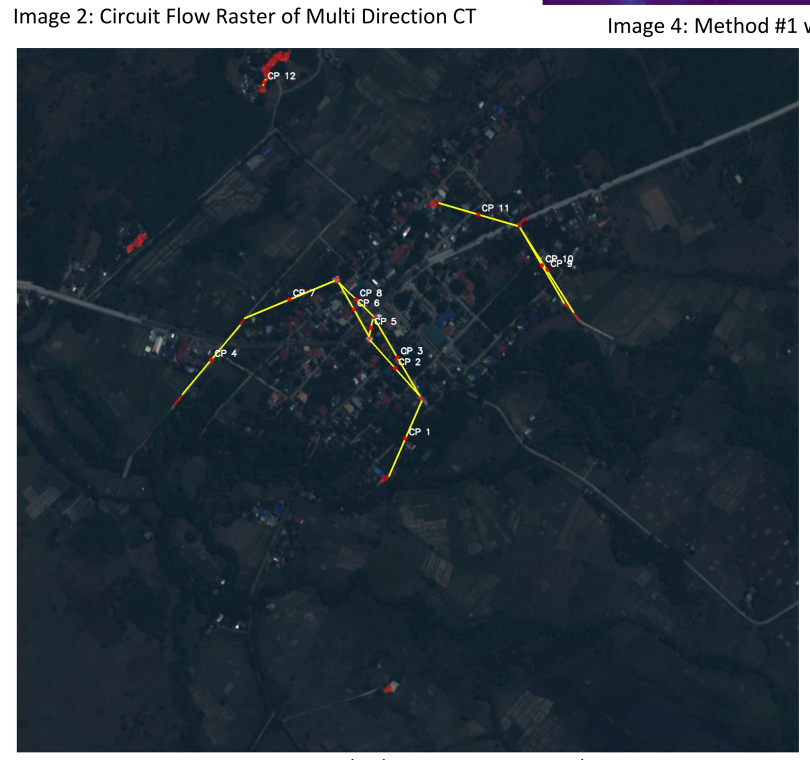


Image 7: Method #3 Pure CV Approach

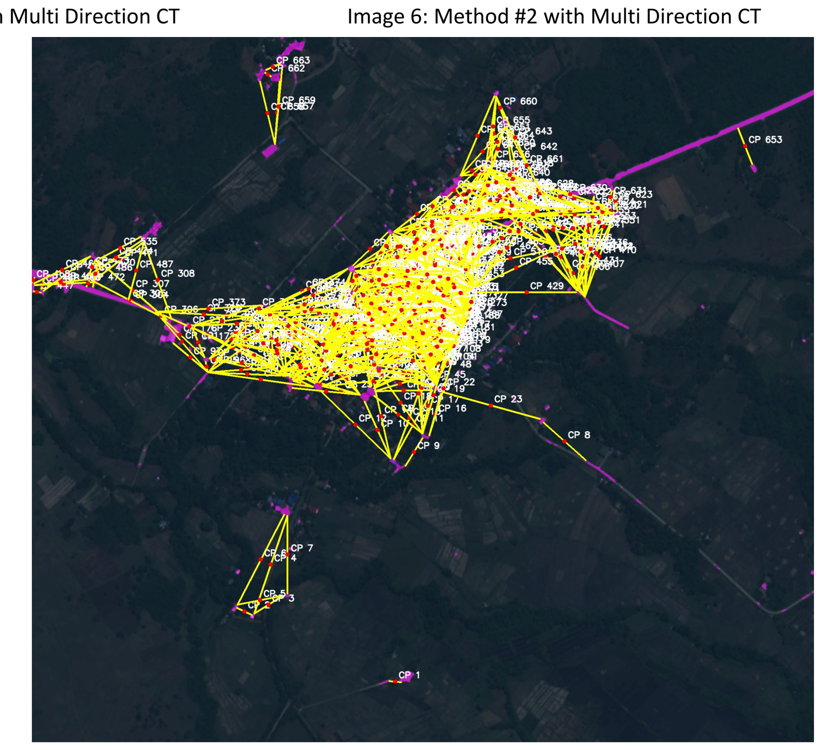


Image 8: Method #4 Semantic K-Means Clustering

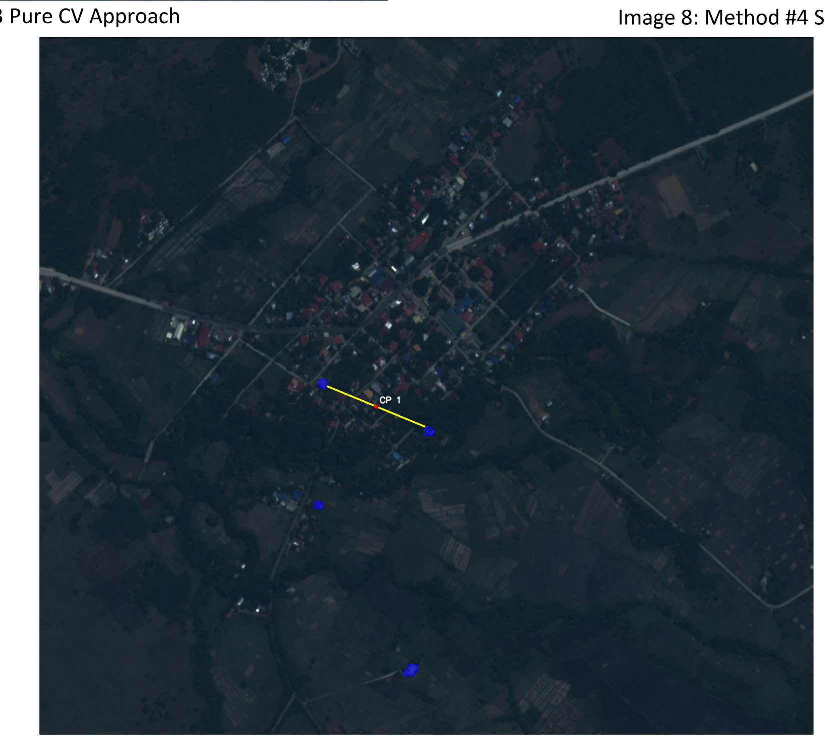


Image 9: Method #5 Zero-Shot FastSAM Approach

Conclusion

Approach Type	Analytical Conclusion
1. Base Circuit Extraction	Highly effective for macro-routing but sensitive to noise. It cleanly isolated bottlenecks in single-directional simulations, but introducing multidirectional flow created excessive mathematical noise, causing the extraction polygons to lose their tight precision.
2. Circuit + CV Fusion	The strongest hybrid performer. By incorporating Canny edge detection, it successfully grounded the math in physical reality. However, it inherited the same multidirectional flow vulnerabilities as Approach 1, leading to fragmented permeability scoring in complex intersections.
3. Pure CV (Geometric)	Prone to severe mislabeling (False Positives). Because it relied strictly on measuring geometric gaps without understanding what the obstacles were, it incorrectly labeled tight, non-tactical spaces (like alleys between residential houses) as major chokepoints.
4. Semantic CV (K-Means)	Aggressive over-correction (Overlabeled). While the morphological closing successfully eliminated the residential false positives from Approach 3, it merged too many features together. This created massive, unusable blockade zones that masked genuine, navigable narrow passages.
5. Foundation Model (FastSAM)	Highly context-aware but overly strict (Underlabeled). The zero-shot AI perfectly segmented real-world objects, completely solving the "residential house" problem natively. However, its strict segmentation thresholds caused it to miss subtle, complex structural bottlenecks that the algorithmic models caught.

Future Work

1. **Implement a Hybrid AI-Algorithmic Architecture:** Combine FastSAM’s object detection with algorithmic edge calculations to filter out residential false positives while preserving subtle, tactical bottlenecks. To be able to merge the semantic intelligence of deep learning with the raw mathematical precision of algorithmic computer vision.
2. **Extract Complex Geometric Features using SAM:** Refine the Segment Anything Model (SAM) to specifically identify and extract non-standard road structures, such as roundabouts, directly from high-resolution satellite imagery.
3. **Integrate Dynamic Pathfinding and Routing:** Use the calculated "Visual Permeability Scores" as tactical friction maps to run advanced routing algorithms (e.g., A* search), simulating realistic vehicle movement through the extracted chokepoints.

Acknowledgments/ References

1. U.S. Army ERDC. *Choke Point Extractor Repository*. GAP / Terrain Human Influence. GitLab (Internal).
2. Electrical4U. *Circuit Theory Fundamentals*. electrical4u.com/electrical-engineering-articles/circuit-theory.
3. Ultralytics. *Fast Segment Anything Model (FastSAM)*. docs.ultralytics.com/models/fast-sam.