

fastgeotoolkit: A High-Performance Geospatial Analysis Library and Novel Route Density Mapping Implementation

Alexander Akira Weimer¹ and Justin Abraham¹

¹ University of Minnesota

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Software

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Summary

fastgeotoolkit is a high-performance JavaScript library that introduces a novel segment-based approach to GPS trajectory analysis and route density visualization.

This library addresses several key limitations of existing approaches to route density visualization, leveraging a segment-based algorithm that processes GPS trajectories as sequences of connected line segments. By analyzing route overlap at the segment level, fastgeotoolkit produces density visualizations that better reflect route usage patterns.

The implementation is able to run on the web or locally, and handles heavy datasets well. As a result, it is a tool accessible for both research and consumer-facing development applications.

Statement of Need

GPS route density visualization is essential for transportation research (Chan et al., 2025), urban planning (Feng et al., 2020), trail management (Shi et al., 2023), and movement ecology (Seidel et al., 2018). Accurate route usage quantification supports evidence-based infrastructure decisions and mobility behavior analysis.

Research Gap in Route-Based Analysis

Current geospatial analysis treats GPS trajectories as point collections, applying kernel density estimation or clustering algorithms (Xu et al., 2024). This introduces several problems when dealing with data where the linear route is the primary feature.

Sampling bias amplification: GPS sampling rates vary by device settings and signal conditions (Müller et al., 2022). Point-based methods make these inconsistencies worse, preventing accurate route comparison across datasets (Xu et al., 2024).

Parameter sensitivity: Results change dramatically based on kernel bandwidth and grid size choices (Thierry et al., 2013), making it difficult to establish consistent analysis methods across studies.

Software Ecosystem Limitations

Inadequate existing tools: Popular GIS software (QGIS (QGIS Contributors, 2022), R spatial packages (Pebesma, 2018; Pebesma & Bivand, 2005), Python scipy (Virtanen et al., 2020)) focus on static point analysis, not linear route patterns.

Computational barriers: Most trajectory tools require preprocessing or server infrastructure (Chan et al., 2025), limiting research accessibility.

36 **Proprietary algorithms:** Commercial platforms like Strava use linear route processing ([Zhang](#)
37 [et al., 2023](#)) but keep implementations closed, creating gaps in open science.

38 **Research Contribution**

39 fastgeotoolkit provides the first open-source, segment-based route density algorithm for GPS
40 track data, enabling: (1) sampling-rate-independent frequency estimation, (2) browser-native
41 analysis workflows, and (3) standardized trajectory analysis methodologies.

42 **Implementation**

43 fastgeotoolkit addresses issues with existing heatmap implementations by treating GPS tracks
44 as sequences of connected segments rather than point clouds. This approach provides more
45 accurate route frequency analysis, and fastgeotoolkit implements it in such a way that it
46 enables processing millions of tracks without preprocessing or server-side infrastructure.

47 **Segment-Based Algorithm**

48 fastgeotoolkit's core algorithm processes GPS tracks in three steps:

49 **Track segmentation:** GPS tracks are split into consecutive coordinate pairs representing
50 individual route segments. Each segment connects two adjacent GPS points, preserving the
51 linear structure of the original path.

52 **Coordinate normalization:** To handle GPS measurement noise, coordinates are snapped to a
53 tolerance grid. This reduces minor variations from GPS accuracy limitations while maintaining
54 route integrity with high fidelity.

55 **Frequency calculation:** Each segment is converted to a normalized string key for efficient
56 storage and lookup. A hash map tracks how many times each unique segment appears across all
57 input tracks. Each track's final frequency is the average frequency of its constituent segments.

58 This approach ensures route popularity reflects actual overlapping usage rather than GPS
59 sampling artifacts. Routes that share the same path segments will have higher frequencies,
60 while unique routes will have lower frequencies.

61 **Performance and Architecture**

62 The algorithm runs in $O(n \times m)$ time where n is the number of tracks and m is the average
63 track length. Hash map lookups provide $O(1)$ average-case performance for frequency queries.

64 The core implementation is written in Rust for memory safety and performance, then compiled
65 to WebAssembly using wasm-pack. This enables browser-native execution without server depen-
66 dencies while maintaining near-native computational speed ([Jung et al., 2023](#); [WebAssembly](#)
67 [Core Specification, 2019](#)).

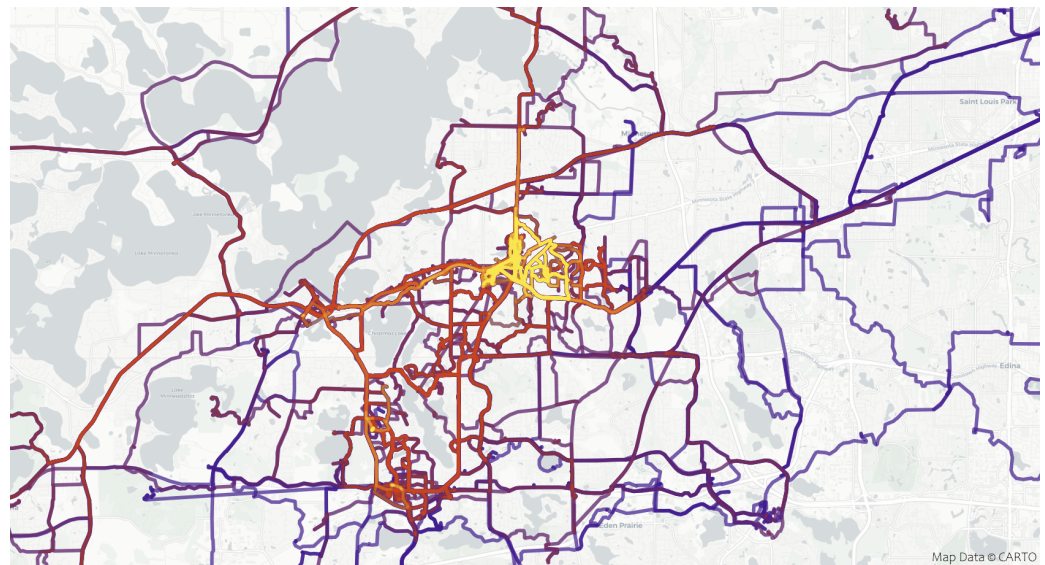


Figure 1: Example heatmap produced using fastgeotoolkit and MapLibre GL JS.

68 The library is distributed as an npm package¹ with TypeScript definitions, integrating naturally
69 with existing JavaScript mapping libraries like Leaflet and MapLibre GL JS ([leaflet](#), 2025;
70 [maplibre-gl-js](#), 2025). This allows for easy use in webapps as seen in [Figure 1](#), a screenshot
71 from the demo page for fastgeotoolkit.

72 Conclusion

73 fastgeotoolkit provides a practical solution for GPS route analysis by focusing on segments
74 rather than points. This approach produces more accurate route density visualizations while
75 being accessible through standard JavaScript tooling.

76 The segment-based algorithm handles the inherent challenges of GPS data, especially mea-
77 surement noise, variable sampling rates, and device differences, without requiring complex
78 preprocessing. fastgeotoolkit implements this approach while remaining highly performant,
79 which makes it largely unique in the landscape of GIS tooling for the web.

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