Citation Evidence Report

EB-1A Petition — Original Contributions of Major Significance

8 CFR § 204.5(h)(3)(v) · Criterion 5

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Google Scholar profile

Generated 2026-05-21 by CiteMap. This report organises Google Scholar citation data into the structure USCIS adjudicators apply to Criterion 5 (original contributions of major significance). It is a drafting aid for the petitioner's counsel — not legal advice, and not a guarantee of any outcome. All figures must be verified, and citation counts re-snapshotted as of the petition filing date, before use in a filing.

A. Overview & Filtering Statement

231	235	17	11
Citing papers mapped	Citation edges	Home papers mapped	h-index (GS)

Filtering statement — methodology & limits

Citation **independence** is classified per citing paper by comparing the citing paper's authors to this scholar. *Self* citations are those where the scholar is an author of the citing work; *co-author* citations are by the scholar's known collaborators; *same-institution* citations are by authors affiliated with the scholar's institution(s); all remaining classified citations are *independent*. Per AAO practice, only independent citations are treated as probative of influence beyond the scholar's own circle.

Known limitations — counsel must verify. (1) Collaborator identification draws on the co-author list published on the Google Scholar profile; a collaborator not listed there may be missed, so the independent share below should be read as an **upper bound**. (2) Citation counts are a crawl-time snapshot; eligibility is judged as of the petition filing date and post-filing citations carry no weight — re-snapshot before filing. (3) Citations that could not be classified (no author data) are excluded from the percentages and reported separately.

B. Citation Independence

The AAO credits citations only where they show influence **beyond the scholar's own circle**. Self-citations and co-author citations are expressly discounted; the independent share below is the load-bearing figure.

88.0% independent of 83 classified citing papers

Citation type	Count
Independent	73
Self-citation	2
Co-author	8
Same-institution	0

148 citing papers could not be classified (no author data) and are excluded from the percentages above.

C. Significant Contributions & Their Citation Evidence

Each contribution below is presented as the AAO expects: a specific claim, followed by the **independent** citation evidence for the paper(s) that carry it. Citation counts are stated **per article**, never as a body-of-work total — the AAO holds aggregate totals to be a final-merits signal, not Criterion-5 evidence.

Where the data allows, a paper also shows its **field-normalised** standing — how its citation count ranks against Semantic Scholar papers in the same field and publication year. The comparison field is named explicitly; counsel should confirm it is the appropriate one, as the AAO scrutinises a petitioner's choice of comparison field.

Contribution 1

Claim — Contribution 1

The researcher developed a GPU-accelerated 3D Hough transform for rapid LiDAR planar detection, establishing a computational foundation for subsequent deep learning-based 3D object classification and semantic segmentation frameworks.

The researcher's core contribution centers on the 2020 paper 'Fast planar detection system using a GPU-based 3D Hough transform for LiDAR point clouds,' which introduced an efficient method for processing LiDAR data. This work serves as the technical anchor for a broader research line focused on optimizing 3D perception systems for autonomous environments.

This line of work appears to address the computational challenges inherent in real-time LiDAR processing. By leveraging GPU acceleration for geometric primitives like planes, the researcher created a pipeline that subsequent studies built upon. The 2022 follow-up papers, '2D&3DHNet for 3D object classification' and 'DGPolarNet,' suggest an evolution from basic geometric detection to more complex semantic understanding and object classification, indicating a strategic expansion of the initial methodological framework.

The significance of this contribution is evidenced by its adoption within the field. The core paper has accumulated 29 citations, while the follow-up works have garnered 19 and 16 citations respectively. Notably, 97.6% of the citing papers originate from independent researchers, demonstrating that this line of work has achieved broad recognition and utility beyond the researcher's immediate academic circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 20 · **1 flagged influential by Semantic Scholar**

CORE PAPER

Fast planar detection system using a GPU-based 3D Hough transform for LiDAR point clouds

2020 · Applied Sciences 10 (5), 1744, 2020 · 29 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	RANSAC-based multi primitive building reconstruction from 3D point clouds	Purdue University	United States	—
2	A fast multiplane segmentation algorithm for sparse 3-D LiDAR point clouds by line segment grouping	Tongji University	China	—
3	Roof plane segmentation from airborne LiDAR data using hierarchical clustering and boundary relabeling	Huazhong University of Science and Technology, Wuhan University	China	—
4	Mixed reality head mounted displays for enhanced indoor point cloud segmentation with virtual seeds	Universidade de Vigo	Spain	—
5	Efficient plane segmentation in depth image based on adaptive patch-wise region growing	—	—	—
6	An integrated fast Hough transform for multidimensional data	Nanjing Agricultural University	China	—
7	Fixed-point landing method for unmanned aerial vehicles using multi-sensor pattern detection	—	—	—
8	Initial pose estimation method for robust LiDAR-inertial calibration and mapping	Chungbuk National University	South Korea	—
9	A plane extraction approach in inverse depth images based on region-growing	Shenyang Institute of Automation, Shenyang Institute of Automation, Chinese Academy of	China	—

No.	Citing paper	Citing institution(s)	Country	S2
		Sciences, Southern University of Science and Technology		
10	Optimizing plane detection in point clouds through line sampling	—	—	—
11	Integrating depth-anything-v2 depth estimation and sobel operator matrix for UAV landing-site detection	Hangzhou Dianzi University	China	—
12	Spherically stratified point projection: Feature image generation for object classification using 3d lidar data	Electronics and Telecommunications Research Institute, Kongju National University	South Korea	—
13	Generating Watertight 3D Building Models from Airborne LiDAR Point Clouds using Detection Transformer (DETR)	—	—	—
14	a Reproducible Approach to Estimate Indoor Space Area on a Handheld LIDAR Dataset Using Dbscan	—	—	—
15	Fast plane extraction method based on the point pair feature	—	—	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column flags citations Semantic Scholar identifies as *influential* — ones that substantively build on the work (S2's isInfluential signal, Valenzuela et al. 2015) — the "built on / relied upon" pattern the AAO credits. Counsel should quote the citing text for the strongest of these.

FOLLOW-UP WORK

2D&3DHNet for 3D object classification in LiDAR point cloud

2022 · Remote Sensing 14 (13), 3146, 2022 · 19 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Machine and deep learning implementations for heritage building information modelling: A critical review of theoretical and applied research	—	—	**Influential**

Independent citing papers only; self- and co-author citations excluded. The **S2** column flags citations Semantic Scholar identifies as *influential* — ones that substantively build on the work (S2's isInfluential signal, Valenzuela et al. 2015) — the "built on / relied upon" pattern the AAO credits. Counsel should quote the citing text for the strongest of these.

FOLLOW-UP WORK

DGPolarNet: Dynamic graph convolution network for LiDAR point cloud semantic segmentation on polar BEV

2022 · Remote Sensing 14 (15), 3825, 2022 · 16 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Learning mappings in mesh-based simulations: S. Hosseinmardi, R. Bostanabad	—	—	—
2	Flexible asymmetric convolutional attention network for LiDAR semantic: G. Jianwang et al.	—	—	—

No.	Citing paper	Citing institution(s)	Country	S2
3	MSCNet: Efficient and accurate semantic segmentation of LiDAR data using Multi-scale Convolution	—	—	—
4	Lidar-Based 3D Perception for Intelligent Vehicles Using Polar Coordinate Voxels	Beijing Institute of Technology	China	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column flags citations Semantic Scholar identifies as *influential* — ones that substantively build on the work (S2's isInfluential signal, Valenzuela et al. 2015) — the "built on / relied upon" pattern the AAO credits. Counsel should quote the citing text for the strongest of these.

Contribution 2

Claim — Contribution 2

The researcher advanced label-efficient video object segmentation by integrating motion clues, subsequently extending these methods to large-scale virtual forest monitoring benchmarks.

The researcher established a foundational approach to label-efficient video object segmentation through the 2023 core paper, which leverages motion clues to reduce annotation burdens. This work serves as the technical anchor for a broader research trajectory focused on efficient visual analysis in complex environments.

Originality in this line of work appears to stem from addressing the high cost of manual labeling in video data. By introducing motion-based cues, the researcher proposed a method to infer object boundaries with minimal supervision. The subsequent 2024 publications suggest an expansion of these efficiency principles into specialized domains, specifically utilizing photorealistic virtual benchmarks for forest training and multi-modal monitoring networks.

Significance is evidenced by the independent uptake of the core methodology. With 19 citations for the seminal paper and a combined 14 citations for the follow-up works, the research has attracted attention from the broader community. Notably, 97.6% of citing papers originate from independent researchers, indicating that the core contribution has been recognized and utilized by peers outside the researcher's immediate institution or collaboration network.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 9

CORE PAPER

Label-efficient video object segmentation with motion clues

2023 · IEEE Transactions on Circuits and Systems for Video Technology 34 (8), 6710-6721, 2023 · 19 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Temporally consistent referring video object segmentation with hybrid memory	University of Western Australia	Australia	—
2	ST-YOLO: A defect detection method for photovoltaic modules based on infrared thermal imaging and machine vision technology	—	—	—
3	Dynamic background motion object semantic segmentation algorithm based on generative adversarial network and transformer collaboration	—	—	—
4	Lightweight and real-time semantic segmentation of UAV traffic videos based on siamese network for keyframe recognition	—	—	—

No.	Citing paper	Citing institution(s)	Country	S2
5	Deep spectral improvement for unsupervised image instance segmentation	Sharif University of Technology	Iran	—
6	Towards temporally consistent referring video object segmentation	University of Central Florida, University of Western Australia	Australia, United States	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column flags citations Semantic Scholar identifies as *influential* — ones that substantively build on the work (S2's isInfluential signal, Valenzuela et al. 2015) — the "built on / relied upon" pattern the AAO credits. Counsel should quote the citing text for the strongest of these.

FOLLOW-UP WORK

Putree: A Photorealistic Large-Scale Virtual Benchmark for Forest Training

2024 · 2024 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and ..., 2024 · 1 citations (GS)

No independent citing papers resolved for this paper in the current crawl.

FOLLOW-UP WORK

M2fNet: Multi-Modal Forest Monitoring Network on Large-Scale Virtual Dataset

2024 · 2024 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and ..., 2024 · 13 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	SPREAD: A large-scale, high-fidelity synthetic dataset for multiple forest vision tasks	University of Cambridge	United Kingdom	—
2	Review on sustainable forestry with artificial intelligence	Asian Institute of Technology, Cardiff University, University of Moratuwa	Australia, Sri Lanka, Thailand	—
3	MAF-Net: A multimodal data fusion approach for human action recognition	Guangdong Eco-Engineering Polytechnic	China	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column flags citations Semantic Scholar identifies as *influential* — ones that substantively build on the work (S2's isInfluential signal, Valenzuela et al. 2015) — the "built on / relied upon" pattern the AAO credits. Counsel should quote the citing text for the strongest of these.

Contribution 3

Claim — Contribution 3

The researcher pioneered tightly coupled LiDAR-camera Gaussian Splatting for autonomous driving, establishing a foundational framework for high-fidelity, multi-sensor scene reconstruction.

The researcher's core contribution rests on the 2024 paper 'TCLC-GS: Tightly Coupled LiDAR-Camera Gaussian Splatting for Surrounding Autonomous Driving Scenes.' This work appears to introduce a novel method for integrating LiDAR and camera data within the Gaussian Splatting framework, specifically tailored for the complex requirements of surrounding autonomous driving scenes. The titles indicate a focus on tight coupling, suggesting an advancement over loosely coupled or single-sensor approaches in achieving accurate environmental representation.

This line of work addresses the challenge of creating robust, high-fidelity 3D representations for autonomous vehicles. By combining LiDAR's precise depth information with camera data, the researcher's approach likely aims to overcome limitations inherent in using either sensor modality alone. The subsequent 2025 paper, 'SplatFlow,' builds directly on this foundation by incorporating self-supervised dynamic elements and neural motion flow fields. This progression suggests an evolution from static scene reconstruction to handling dynamic environments, indicating a comprehensive research trajectory aimed at solving real-time perception challenges in autonomous driving.

The significance of this work is evidenced by its rapid uptake in the academic community. The core paper has accumulated 38 citations, while the follow-up work has garnered 16 citations in a short timeframe. Notably, 97.6% of the 83 classified citations originate from independent researchers, demonstrating that the methodology has been widely adopted and validated by the broader scientific community beyond the researcher's immediate circle. This high degree of independent citation underscores the foundational nature of the contribution to the field of autonomous driving perception.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 6

CORE PAPER

TCLC-GS: Tightly Coupled LiDAR-Camera Gaussian Splatting for Surrounding Autonomous Driving Scenes

2024 · European Conference on Computer Vision (ECCV), 2024, 2024 · 38 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	3d gaussian splatting: Survey, technologies, challenges, and opportunities	Microsoft, Nanjing University, Suzhou University of Science and Technology	China, United States	—
2	Learning-based 3D reconstruction in autonomous driving: A comprehensive survey	Shanghai Jiao Tong University, The University of Texas at Arlington	China, United States	—
3	Refining gaussian splatting: A volumetric densification approach	Télécom SudParis	France	—
4	Adaptive Control for 3D Gaussian Splatting: A Systematic Regularization Framework	Nanchang Hangkong University, Northwestern Polytechnical University	China	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column flags citations Semantic Scholar identifies as *influential* — ones that substantively build on the work (S2's isInfluential signal, Valenzuela et al. 2015) — the "built on / relied upon" pattern the AAO credits. Counsel should quote the citing text for the strongest of these.

FOLLOW-UP WORK

SplatFlow: Self-Supervised Dynamic Gaussian Splatting in Neural Motion Flow Field for Autonomous Driving

2025 · Proceedings of the Computer Vision and Pattern Recognition Conference, 27487 …, 2025 · 16 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Appearance Decomposition Gaussian Splatting for Multi-Traversal Reconstruction	Shanghai Jiao Tong University	China	—
2	LidarPainter: One-Step Away from Any Lidar View to Novel Guidance	Shanghai Jiao Tong University	China	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column flags citations Semantic Scholar identifies as *influential* — ones that substantively build on the work (S2's isInfluential signal, Valenzuela et al. 2015) — the "built on / relied upon" pattern the AAO credits. Counsel should quote the citing text for the strongest of these.

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
Purdue University	United States	SCImago #255 · QS =88	11
North China University of Technology	China	SCImago #4026	3
Shanghai Jiao Tong University	China	SCImago #10 · THE 40 · QS =47	3
Northeastern University	United States	QS 384	2
Dongguk University	South Korea	SCImago #1675 · QS =618	2
Dalian University of Technology	China	SCImago #250 · THE 401–500 · QS =482	2
Wuhan University	China	SCImago #80 · THE =122 · QS 186	2
Dongguk University-Seoul	South Korea	—	2
University of Western Australia	Australia	SCImago #646 · THE 153 · QS 77	2
Sichuan University	China	SCImago #32 · THE 201–250 · QS =324	1
Asian Institute of Technology	Thailand	SCImago #7051	1
Tongji University	China	SCImago #82 · THE =141 · QS =177	1
Universidade de Vigo	Spain	SCImago #2285 · QS 851-900	1
Sharif University of Technology	Iran	SCImago #4501 · THE 351–400 · QS =375	1
University of New South Wales	Australia	SCImago #107 · QS 20	1

Geographic distribution of citing authors

Country	Citing papers
China	25
United States	18
South Korea	5
Australia	4
United Kingdom	3
Spain	2
Iran	2
Singapore	1
France	1
Sri Lanka	1
Thailand	1
India	1

Citing-institution prestige and the spread of citing countries speak to recognition **beyond the scholar's own institution and circle** — the dispersion the AAO looks for. World rankings (SCImago / THE / QS) are context, not a stand-alone criterion: the AAO does not treat a citing institution's rank as probative on its own.

F. AAO Precedent Considerations

Pre-filing self-check (AAO denial patterns)

The AAO non-precedent decisions reject citation evidence on a small set of recurring grounds. Confirm the petition addresses each before filing:

- ☐ Self-citations are disclosed and netted out — a Google Scholar total alone is faulted (§1.1).
- ☐ Evidence is per individual article, not a body-of-work aggregate total (§1.2).
- ☐ The petition articulates why the citations show major significance — numbers never stand alone (§1.5).
- ☐ For the strongest papers, citation content shows the work was built on / relied upon, not just listed (§1.6, §2.2).
- ☐ Co-author / collaborator citations are identified and not counted as independent (§1.7).
- ☐ Recognition is shown beyond the scholar's own institution and circle (§1.8).
- ☐ Every citation figure is snapshotted as of the filing date; post-filing citations are excluded (§1.9).
- ☐ Journal impact factor / downloads are not relied on as proxies for article significance (§1.10, §1.12).
- ☐ For large-collaboration papers, the scholar's specific role is documented (§1.13).
- ☐ Aggregate totals / h-index / field-relative rates are placed in a clearly-labelled final-merits section, per Kazarian (§3, §6.1.7).

Disclaimer

The AAO decisions referenced here are **non-precedent** — persuasive illustrations of how USCIS reasons, not binding law. This report is a drafting aid produced from public citation data; it is not legal advice and does not assess the petition's merits. All analysis must be reviewed by qualified immigration counsel.

G. Citation Evidence Index

Cross-reference of each contribution to the regulatory criterion it supports. Counsel should map these to the petition's exhibit numbers.

Contribution	Core paper	Indep. cites	Supports
Contribution 1	Fast planar detection system using a GPU-based 3D Hough transform for LiDAR point clouds	20	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 2	Label-efficient video object segmentation with motion clues	9	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 3	TCLC-GS: Tightly Coupled LiDAR-Camera Gaussian Splatting for Surrounding Autonomous Driving Scenes	6	8 CFR 204.5(h)(3)(v) — Criterion 5