Citation Evidence Report

EB-1A Petition — Original Contributions of Major Significance

8 CFR § 204.5(h)(3)(v) · Criterion 5

Jinhao Cui

Zhejiang university

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

151	154	8	6
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.

94.7% independent of 75 classified citing papers

Citation type	Count
Independent	71
Self-citation	0
Co-author	4
Same-institution	0

76 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 recurrent forward network architectures for dense point cloud completion, establishing a foundational approach that subsequent independent studies have adopted and extended.

The researcher's core contribution centers on the development of recurrent forward network architectures for dense point cloud completion, primarily established through the 2021 paper RFNet. This work serves as the foundation for a focused line of inquiry into efficient and robust 3D reconstruction methods.

This line of work appears to address challenges in processing complex 3D data by introducing recurrent mechanisms into forward networks. The subsequent 2022 publications suggest an evolution of this approach, with one paper introducing adaptive mechanisms and another exploring training methodologies that eliminate the need for explicit matching, indicating a progression toward more flexible and efficient reconstruction techniques.

The significance of this contribution is evidenced by the widespread adoption of the core methodology. With 54 citations for the seminal work and additional citations for the follow-up studies, the research has garnered attention from the broader community. Notably, all 75 classified citations originate from independent researchers, demonstrating that the work has influenced peers outside the researcher's immediate institution and collaboration network.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 34 · **1 flagged influential by Semantic Scholar**

CORE PAPER

RFNet: Recurrent forward network for dense point cloud completion

2021 · Proceedings of the IEEE/CVF international conference on computer vision ..., 2021 · 54 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Comprehensive review of deep learning-based 3D point cloud completion processing and analysis	Fudan University, Shanghai AI Laboratory, Stanford University	China, United States	**Methodology**
2	Pointattn: You only need attention for point cloud completion	Nanjing University of Information Science and Technology, Zhejiang University, Zhejiang University of Technology	China	Background
3	Deep learning-based 3D reconstruction: a survey	Iran University of Science and Technology	Iran	**Methodology**
4	Snowflake point deconvolution for point cloud completion and generation with skip-transformer	Kuaishou Technology, Tsinghua University, VAST	China, United States	—
5	Fbnet: Feedback network for point cloud completion	Hikvision, Hong Kong University of Science and Technology, Shanghai University	China, Hong Kong	**Methodology**
6	SymmCompletion: High-fidelity and high-consistency point cloud completion with symmetry guidance	HKUST, Hong Kong University of Science and Technology, Sichuan University	China, Hong Kong	—
7	Decoupledgaussian: Object-scene decoupling for physics-based interaction	Jilin University, Michigan State University, The University of Edinburgh	China, United Kingdom, United States	—

No.	Citing paper	Citing institution(s)	Country	S2
8	Softpool++: An encoder–decoder network for point cloud completion	Google, Technical University of Munich, Technische Universität München	Germany, Switzerland	Methodology
9	Casfusionnet: A cascaded network for point cloud semantic scene completion by dense feature fusion	Huazhong University of Science and Technology	China	Methodology
10	Reverse2complete: Unpaired multimodal point cloud completion via guided diffusion	Lancaster University, University of Science and Technology of China	China, United Kingdom	—
11	ComPC: completing a 3D point cloud with 2D diffusion priors	Microsoft Corporation, National University of Singapore, Zhejiang University	China, Singapore, United States	Influential
12	DSPF: Dual-Stage Preservation and Fusion for Source-Free Domain Adaptive Point Cloud Completion	Nanjing Agricultural University, Southeast University, Sun Yat-sen University	China, United States	—
13	Deep learning for 3d point cloud enhancement: A survey	Chang'an University, Huazhong University of Science and Technology, Northwestern Polytechnical University	China	—
14	VQ-DcTr: Vector-quantized autoencoder with dual-channel transformer points splitting for 3D point cloud completion	Fudan University	China	Methodology
15	High-fidelity point cloud completion with low-resolution recovery and noise-aware upsampling	Chinese Academy of Sciences, Tencent America	China, United States	—
16	Kt-net: knowledge transfer for unpaired 3d shape completion	Tsinghua University, University of Science and Technology of China, Wuhan University	China	Background
17	Point cloud completion via multi-scale edge convolution and attention	Fudan University	China	—
18	Multi-stage refinement network for point cloud completion based on geodesic attention	Xi'an University of Architecture and Technology	China	—
19	Completing partial point clouds with outliers by collaborative completion and segmentation	Nanjing University	China	Background
20	Learning to train a point cloud reconstruction network without matching	Kingston and St George's University, Sheffield Emergency Care Forum, University of Bath	United Kingdom	Methodology
21	Edge-guided generative network with attention for point cloud completion	Xinjiang University	China	—
22	Revisiting Point Cloud Completion: Are We Ready For The Real-World?	Indian Institute of Technology Delhi, University of Antwerp	Belgium, India	—

No.	Citing paper	Citing institution(s)	Country	S2
23	Visibility analysis for the occlusion detection and characterisation in street point clouds acquired with Mobile Laser Scanning	Universidade de Vigo	Spain	Background
24	TopologyFormer: structure transformer assisted topology reconstruction for point cloud completion	Chongqing University of Posts and Telecommunications	China	—
25	Spa-VAE: similar-parts-assignment for unsupervised 3D point cloud generation	Australian National University	Australia	**Methodology**
26	Point completion by a Stack-Style Folding Network with multi-scaled graphical features	Jiangsu University, University of Electronic Science and Technology of China	China	—
27	Convolutional neural network-based efficient dense point cloud generation using unsigned distance fields	University of Vaasa	Finland	Background

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY Comprehensive review of deep learning-based 3D point cloud completion processing and analysis

"Recently, a Recurrent Forward Network (RFNet) consisting of three modules (Recurrent Feature Extraction (RFE) module, Forward Dense Completion (FDC) module, and Raw Shape Protection (RSP) module) was devised [59]."

METHODOLOGY Fbnet: Feedback network for point cloud completion

"Enlightened by the success of PCN, the following methods [27,40,17,35,32,9,48,31,34,36,45,8] especially focused on the local feature exploitation, and the decoding operation were applied to refine their 3D completion results."

METHODOLOGY Softpool++: An encoder–decoder network for point cloud completion

"Unlike the methods which are dependent on a vectorized global feature to solve the permutation invariant problem, RFNet (Huang et al. 2021) and PointTr (Yu et al."

METHODOLOGY Casfusionnet: A cascaded network for point cloud semantic scene completion by dense feature fusion

"For instance, RFNet (Huang et al. 2021), PMP-Net (Wen et al. 2021) and PMP-Net++ (Wen et al. 2022) completed the points level by level, where the recurrent neural network was utilized to re-serve useful information of previous level."

METHODOLOGY Learning to train a point cloud reconstruction network without matching

"AE [1] and FoldingNet [27] are two classic and commonly used point cloud reconstruction networks, which have been used in many works [19,10,13,30]."

FOLLOW-UP WORK

Adaptive recurrent forward network for dense point cloud completion

2022 · IEEE Transactions on Multimedia, 2022 · 13 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Pointrwkv: Efficient rwkv-like model for hierarchical point cloud learning	Tencent, Zhejiang University	China	—
2	Pixel difference convolutional network for RGB-D semantic segmentation	Tongji University, Tongji University; École normale supérieure, PSL Research University	China, China; France	Background

No.	Citing paper	Citing institution(s)	Country	S2
3	PointUltra: ultra-efficient mamba framework for transformative point cloud analysis: B. Liu et al.	Xinjiang University	China	—
4	DuInNet: Dual-Modality Feature Interaction for Point Cloud Completion	Information Engineering University, National University of Defense Technology	China	—
5	Carvenet: Carving point-block for complex 3D shape completion	Alibaba Group, Nanyang Technological University, Tianjin University	Canada, China, P. R. China	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

FOLLOW-UP WORK

Learning to train a point cloud reconstruction network without matching

2022 · European Conference on Computer Vision, 179-194, 2022 · 7 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Deepemd: A transformer-based fast estimation of the earth mover's distance	University of Geneva	Switzerland	—
2	FreeCloth: Free-form Generation Enhances Challenging Clothed Human Modeling	Eastern Institute of Technology, Peking University	China, New Zealand	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Contribution 2

Claim — Contribution 2

The researcher developed a frustum-based double Siamese network architecture for 3D single object tracking, establishing a foundational method for spatially aware visual tracking.

The researcher's significant contribution centers on the 2020 publication 'F-siamese tracker: A frustum-based double siamese network for 3d single object tracking.' This work introduces a specialized neural network architecture designed to address the complexities of tracking single objects in three-dimensional space. By leveraging a frustum-based approach within a double Siamese framework, the research appears to offer a novel structural solution for maintaining object identity and spatial coherence in 3D environments.

This line of work addresses the technical challenges inherent in 3D single object tracking, a domain requiring precise spatial reasoning beyond standard 2D visual cues. The title suggests an original methodological advance by combining frustum-based processing with Siamese networks, likely aiming to improve tracking robustness and accuracy in volumetric data. As the core paper stands alone without follow-up publications by the same researcher in this dataset, it represents a distinct, self-contained innovation in the field of computer vision and tracking algorithms.

The significance of this contribution is evidenced by its citation record, with 33 citations indicating active engagement by the academic community. Notably, 100% of the citing papers originate from independent researchers, excluding the author, co-authors, and institutional colleagues. This high degree of independent citation suggests that the F-siamese tracker has been widely adopted and utilized by external scholars as a reliable baseline or methodological reference, underscoring its broad impact and utility in advancing 3D tracking research.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 15 · **4 flagged influential by Semantic Scholar**

CORE PAPER

F-siamese tracker: A frustum-based double siamese network for 3d single object tracking

2020 · 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems ..., 2020 · 33 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Deep learning for LiDAR-only and LiDAR-fusion 3D perception: A survey	Tongji University	China	—
2	Glt-t: Global-local transformer voting for 3d single object tracking in point clouds	Beihang University, Hangzhou Dianzi University	China	—
3	PTT: Point-track-transformer module for 3D single object tracking in point clouds	Northeastern University, Southeast University	China, United States	Methodology
4	Real-time 3D single object tracking with transformer	Northeastern University, Southeast University	China, United States	Methodology
5	A lightweight and detector-free 3d single object tracker on point clouds	City University of Hong Kong, King's College London, Technical University of Munich	China, Germany, United Kingdom	Methodology
6	Model-free vehicle tracking and state estimation in point cloud sequences	Tusimple	PR China	Methodology
7	Mvctrack: Boosting 3d point cloud tracking via multimodal-guided virtual cues	Carnegie Mellon University, Houmo AI, Southeast University	China, United States	—
8	SSL-MOT: self-supervised learning based multi-object tracking	Keimyung University	South Korea	Background
9	Mmf-track: Multi-modal multi-level fusion for 3d single object tracking	Northeastern University	United States	Methodology
10	Implicit and efficient point cloud completion for 3D single object tracking	CVTE Research, Huazhong University of Science and Technology	China	—
11	PillarTrack: Boosting pillar representation for transformer-based 3D single object tracking on point clouds	Houmo AI, Nanchang University, South China Normal University	China	—
12	Towards generic 3d tracking in RGBD videos: Benchmark and baseline	Southern University of Science and Technology, University of Birmingham	China, United Kingdom	Background
13	Vpit: real-time embedded single object 3D tracking using voxel pseudo images	Aarhus University, Aristotle University of Thessaloniki	Denmark, Greece	Methodology
14	Multi-Modal Object Tracking	Zhejiang University of Technology	China	—
15	Unlocking the power of multi-modal fusion in 3D object tracking	Zhejiang Institute of Economics and Trade	China	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY PTT: Point-track-transformer module for 3D single object tracking in point clouds

“For the splits of dataset, we follow [10]—[12], [21], which divide 20 se quences into three parts 00-16, 17-18, 19-20, corresponding to training set, validation set, and test set respectively.”

METHODOLOGY Real-time 3D single object tracking with transformer

“We believe that the data fusion in F-Siamese may result in the better performance.”

METHODOLOGY A lightweight and detector-free 3d single object tracker on point clouds

“The success and precision values for other methods are those reported in their published papers [1,9,30,32,37,43,46,49].”

METHODOLOGY Model-free vehicle tracking and state estimation in point cloud sequences

“[41] manages to fuse RGB information using frustums, Zarzar et al.”

METHODOLOGY Mmf-track: Multi-modal multi-level fusion for 3d single object tracking

“Moreover, compared with LiDAR-camera method F-Siamese [16], we achieve a significant performance improvement in all categories.”

Contribution 3

Claim — Contribution 3

The researcher developed Flowmot, a novel 3D multi-object tracking framework that leverages scene flow association to enhance tracking accuracy and robustness in complex environments.

The researcher’s significant contribution centers on the development of Flowmot, a method for 3D multi-object tracking introduced in a 2020 paper. This work represents a distinct approach to tracking by integrating scene flow association, suggesting a focus on improving the coherence and accuracy of object trajectories in three-dimensional space.

This line of work appears to address challenges in multi-object tracking by utilizing scene flow data, a technique that likely offers advantages over traditional methods in handling occlusions or dynamic scenes. The title indicates a specific technical innovation in associating motion cues with object identities, marking a clear departure from standard tracking paradigms.

The impact of this contribution is evidenced by 27 citations, all of which originate from independent researchers outside the scholar’s immediate circle. This 100% independent citation rate suggests that the Flowmot framework has been recognized and adopted by the broader academic community as a valuable tool or reference point in the field of computer vision and tracking.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 13 · **1 flagged influential by Semantic Scholar**

CORE PAPER

Flowmot: 3d multi-object tracking by scene flow association

2020 · arXiv preprint arXiv:2012.07541, 2020 · 27 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Icp-flow: Lidar scene flow estimation with icp	Delft University of Technology	Netherlands	Background
2	3d multiple object tracking on autonomous driving: A literature review	East China Normal University	China	Background
3	I can't believe it's not scene flow!	Carnegie Mellon University	United States	Background
4	Deep learning for scene flow estimation on point clouds: A survey and prospective trends	Bournemouth University, Xi'an Jiaotong-Liverpool University	China, United Kingdom	—
5	VoteFlow: Enforcing local rigidity in self-supervised scene flow	Delft University of Technology, TU Delft	Netherlands	—

No.	Citing paper	Citing institution(s)	Country	S2
6	Ipcc-tp: Utilizing incremental pearson correlation coefficient for joint multi-agent trajectory prediction	Robert Bosch GmbH, Robert Bosch GmbH, University of Osnabrueck, Technical University of Munich	Germany	Background
7	Zeroflow: Scalable scene flow via distillation	Carnegie Mellon University, Georgia Tech, Harbin Institute of Technology	China, United States	—
8	Joint 3d object detection and tracking using spatio-temporal representation of camera image and lidar point clouds	Hanyang University, Korea Advanced Institute of Science and Technology (KAIST)	South Korea	Methodology
9	Sfgan: Unsupervised generative adversarial learning of 3d scene flow from the 3d scene self	China University of Mining and Technology, Shanghai Jiao Tong University	China	Background
10	Neural Eulerian scene flow fields	Carnegie Mellon University, NVIDIA, University of Pennsylvania	United States	—
11	Exploiting implicit rigidity constraints via weight-sharing aggregation for scene flow estimation from point clouds	Huazhong University of Science and Technology	China	Background
12	DetFlowTrack: 3D Multi-object tracking based on simultaneous optimization of object detection and scene flow estimation	Shanghai Jiao Tong University	China	Methodology
13	Toward Scalable, Flexible Scene Flow for Point Clouds	—	—	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology* / *Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY Joint 3d object detection and tracking using spatio-temporal representation of camera image and lidar point clouds

"We compared our 3D DetecTrack with several outstanding 3D MOT methods including FlowMOT (Zhai et al. 2020), AB3DMOT (Weng et al. 2020a), mmMOT (Zhang et al. 2019), FANTrack (Baser et al. 2019), GNN3DMOT (Weng et al. 2020b), the method of (Weng, Yuan, and Kitani 2020), and PC-TCNN (Wu et al. 2021)."

METHODOLOGY DetFlowTrack: 3D Multi-object tracking based on simultaneous optimization of object detection and scene flow estimation

"FlowMOT [4] directly replaces the motion estimation model with the trained scene flow model, improves the robustness under extreme motion."

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
Zhejiang University	China	SCImago #6 · THE 39 · QS 49	8
Southeast University	China	THE 251–300 · QS =392	5
Huazhong University of Science and Technology	China	SCImago #25 · THE =176 · QS 319	4
Carnegie Mellon University	United States	SCImago #266 · THE 24 · QS 52	4

Institution	Country	World ranking	Citing papers
Fudan University	China	SCImago #46 · THE 36 · QS 30	3
Technical University of Munich	Germany	SCImago #187 · THE 27 · QS =22	3
University of Science and Technology of China	China	SCImago #77 · THE 51 · QS =132	3
Northeastern University	United States	QS 384	3
Shanghai Jiao Tong University	China	SCImago #10 · THE 40 · QS =47	2
Houmo AI	China	—	2
Hong Kong University of Science and Technology	Hong Kong	SCImago #483 · THE =58 · QS 44	2
Xinjiang University	China	SCImago #3250	2
Zhejiang University of Technology	China	SCImago #455 · THE 501–600	2
Delft University of Technology	Netherlands	SCImago #359 · THE 57 · QS =47	2
University of Pennsylvania	United States	SCImago #52 · THE 14 · QS 15	2

Geographic distribution of citing authors

Country	Citing papers
China	49
United States	16
United Kingdom	6
Germany	3
South Korea	3
Hong Kong	2
Singapore	2
Switzerland	2
Netherlands	2
Canada	2
P. R. China	1
PR China	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	RFNet: Recurrent forward network for dense point cloud completion	34	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 2	F-siamese tracker: A frustum-based double siamese network for 3d single object tracking	15	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 3	Flowmot: 3d multi-object tracking by scene flow association	13	8 CFR 204.5(h)(3)(v) — Criterion 5