# Citation Evidence Report

EB-2 NIW Petition — National Interest Waiver

Matter of Dhanasar · Prong 2 (well-positioned)


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Google Scholar profile


**Generated 2026-06-08 by CiteMap.** This report organises Google Scholar citation data into the structure USCIS adjudicators apply to Prong 2 of Matter of Dhanasar (the petitioner is well positioned to advance the proposed endeavor) — the prong where past citation evidence is most probative. 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

| 2,733 | 2,908 | 30 | 26 |
|---|---|---|---|
| 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.

**93.3% independent** of 2,164 classified citing papers

| Citation type | Count |
|---|---|
| Independent | 2,020 |
| Self-citation | 27 |
| Co-author | 117 |
| Same-institution | 0 |

569 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 efficient semantic segmentation methods for large-scale point clouds, establishing a foundational framework that enabled subsequent advancements in 3D registration and unsupervised learning.*

The researcher's primary contribution centers on the development of efficient semantic segmentation techniques for large-scale point clouds, anchored by the seminal 2020 paper RandLA-Net. This work serves as the cornerstone for a sustained research trajectory addressing the computational challenges inherent in processing massive 3D data structures.

This line of work appears to address the critical gap in handling the scale and complexity of 3D point cloud data. The progression from RandLA-Net to SpinNet (2021) and GrowSP (2023) suggests a deliberate expansion from segmentation to broader 3D understanding, including general surface descriptors for registration and unsupervised segmentation methods. The titles indicate a focus on creating robust, scalable solutions that generalize across different 3D processing tasks.

The significance of this contribution is evidenced by the substantial uptake of the core work, which has accumulated 2,864 citations. Notably, 93.3% of the citing papers originate from independent researchers, indicating that the methodology has been widely adopted and validated by the broader scientific community beyond the researcher's immediate circle. The continued relevance is further supported by the citation counts of the follow-up papers, demonstrating sustained impact in the field.

**INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 1,244** · **139 flagged influential by Semantic Scholar**

**CORE PAPER**

### RandLA-Net: Efficient Semantic Segmentation of Large-Scale Point Clouds

2020 · 2,864 citations (GS)

Field-normalised: 1,933 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2020 indexed by Semantic Scholar, by citation count.

| No. | Citing paper | Citing institution(s) | Country | S2 |
|---|---|---|---|---|
| 1 | Point transformer v3: Simpler faster stronger | Moscow Institute of Thermal Technology, Peking University, The Chinese University of Hong Kong, Shenzhen | China, Hong Kong, Russia | — |
| 2 | Deep learning for LiDAR-only and LiDAR-fusion 3D perception: A survey | Tongji University | China | — |
| 3 | Deep learning for scene flow estimation on point clouds: A survey and prospective trends | Bournemouth University, Xi'an Jiaotong-Liverpool University | China, United Kingdom | — |
| 4 | Pointseg: A training-free paradigm for 3d scene segmentation via foundation models | Tencent | China | — |
| 5 | Link: Linear kernel for lidar-based 3d perception | Brown University, Nanjing University | China, United States | — |
| 6 | Lidarformer: A unified transformer-based multi-task network for lidar perception | Tusimple, University of Central Florida | PR China, United States | — |
| 7 | Deep-learning-based approaches for semantic segmentation of natural scene images: A review | Ankara University, Tampere University | Finland, Turkey | — |
| 8 | Learning to generate realistic lidar point clouds | University of Illinois at Urbana-Champaign | United States | — |

| No. | Citing paper | Citing institution(s) | Country | S2 |
|---|---|---|---|---|
| 9 | Transfer learning from synthetic to real lidar point cloud for semantic segmentation | Nanyang Technological University | Singapore | — |
| 10 | From slam to situational awareness: Challenges and survey | University of Luxembourg | Luxembourg | — |
| 11 | Efficient 3d deep lidar odometry | Shanghai Jiao Tong University | China | **Influential** |
| 12 | A survey on deep learning fundamentals | Harbin Institute of Technology | China | — |
| 13 | Transformer-based visual segmentation: A survey | Fudan University, Nanyang Technological University, Shanghai AI Laboratory | China, Singapore, United Kingdom | — |
| 14 | Rangevit: Towards vision transformers for 3d semantic segmentation in autonomous driving | Centre de Robotique, Ecole des Ponts, valeo.ai | France | — |
| 15 | Pointnext: Revisiting pointnet++ with improved training and scaling strategies | Amazon, King Abdullah University of Science and Technology (KAUST), Microsoft Research | Saudi Arabia, United States | **Influential** |
| 16 | Ulip: Learning a unified representation of language, images, and point clouds for 3d understanding | Apple, Salesforce, Salesforce AI | United States | — |
| 17 | Rethinking range view representation for lidar segmentation | Nanyang Technological University, National University of Singapore, Shanghai AI Laboratory | China, Singapore | — |
| 18 | Cross-modal unsupervised domain adaptation for 3D semantic segmentation via multi-scale fusion-then-distillation | PLA Army Engineering University | China | — |
| 19 | Searching efficient 3d architectures with sparse point-voxel convolution | Massachusetts Institute of Technology, MIT, Moscow Institute of Thermal Technology | China, Russia, United States | — |
| 20 | Octformer: Octree-based transformers for 3d point clouds | Peking University | China | — |
| 21 | Squeezesegv3: Spatially-adaptive convolution for efficient point-cloud segmentation | Facebook, Meta Research, University of California, Irvine Medical Center | United States | **Influential** |
| 22 | Frnet: Frustum-range networks for scalable lidar segmentation | Nanjing University of Aeronautics and Astronautics, Nanjing University of Information Science and Technology, Nanjing University of Posts and Telecommunications | China, Singapore | — |
| 23 | Enable deep learning on mobile devices: Methods, systems, and applications | Massachusetts Institute of Technology, MIT, Moscow Institute of Thermal Technology | Russia, United States | — |

| No. | Citing paper | Citing institution(s) | Country | S2 |
|---|---|---|---|---|
| 24 | Vehicle detection algorithms for autonomous driving: A review | Harbin Institute of Technology (Shenzhen), Henan University of Technology | China | — |
| 25 | Deep learning based 3D segmentation in computer vision: A survey | Hunan Normal University, Hunan University, The Australian National University | Australia, China | — |
| 26 | Vehicle detection for autonomous driving: A review of algorithms and datasets | University of Science and Technology of China | China | — |
| 27 | 3d-mininet: Learning a 2d representation from point clouds for fast and efficient 3d lidar semantic segmentation | Universidad de Zaragoza | Spain | — |
| 28 | Deep learning on 3d semantic segmentation: A detailed review | National Technical University of Athens, Université de Strasbourg | France, Greece | **Influential** |
| 29 | Deep-learning-based point cloud semantic segmentation: A survey | North China University of Water Resources and Electric Power | China | — |
| 30 | Spiking point transformer for point cloud classification | Tencent Inc., University of Science and Technology of China, Zhejiang University | China | — |

**Showing the 30 most-cited of 808 independent citing papers.**

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**

## SpinNet: Learning a General Surface Descriptor for 3D Point Cloud Registration

2021 · 537 citations (GS)

Field-normalised: 379 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2021 indexed by Semantic Scholar, by citation count.

| No. | Citing paper | Citing institution(s) | Country | S2 |
|---|---|---|---|---|
| 1 | Cmhanet: A cross-modal hybrid attention network for point cloud registration | China Electric Power Research Institute, Xi'an Jiaotong University | China | **Influential** |
| 2 | PointDifformer: Robust point cloud registration with neural diffusion and transformer | Continental Automotive Singapore Pte. Ltd., Nanyang Technological University | Singapore | **Influential** |
| 3 | LiDAR Point Cloud Registration Based on Pyramid Compatibility Graph Optimization With Coarse-to-Fine Feature Extraction | — | — | — |
| 4 | CGReg: Classification-Guided Point Cloud Registration via Equivariant Learning | Zhejiang Normal University, Zhejiang University of Finance and Economics | China | — |

| No. | Citing paper | Citing institution(s) | Country | S2 |
|---|---|---|---|---|
| 5 | Weakly supervised 3d scene segmentation with region-level boundary awareness and instance discrimination | Chinese University of Hong Kong, City University of Hong Kong, The Chinese University of Hong Kong | China, Hong Kong | — |
| 6 | Gipso: Geometrically informed propagation for online adaptation in 3d lidar segmentation | University of Trento | Italy | — |
| 7 | Boosting few-shot 3d point cloud segmentation via query-guided enhancement | Harbin Institute of Technology | China | — |
| 8 | General 3D Vision-Language Model With Fast Rendering and Pre-Training Vision-Language Alignment | California Institute of Technology, Peking University, Tsinghua University | China, United States | — |
| 9 | Weaklabel3d-net: A complete framework for real-scene lidar point clouds weakly supervised multi-tasks understanding | Chinese University of Hong Kong, City University of Hong Kong, Wuhan University | China, Hong Kong | — |
| 10 | Dual-feature attention for robust point cloud registration: integrating transformation-variant and invariant features | Shenzhen University | China | — |
| 11 | A review of non-rigid transformations and learning-based 3D point cloud registration methods | University Hospital Heidelberg | Germany | — |
| 12 | Multiway non-rigid point cloud registration via learned functional map synchronization | NVIDIA, Princeton University, Stanford University | China, United States | — |
| 13 | p^ 3-net: Part mobility parsing from point cloud sequences via learning explicit point correspondence | Baidu Research, Beihang University, State Key Laboratory of Virtual Reality Technology and Systems | China | — |
| 14 | Oaaformer: Robust and efficient point cloud registration through overlapping-aware attention in transformer | Qingdao University of Science and Technology, Shandong University, Shandong University of Science and Technology | China, United States | — |
| 15 | 3D point cloud registration with multi-scale architecture and unsupervised transfer learning | École Nationale Supérieure des Mines de Paris, Université Paris Sciences et Lettres | France | **Influential** |
| 16 | TSG-Seg: Temporal-selective guidance for semi-supervised semantic segmentation of 3D LiDAR point clouds | Nanyang Technological University, Nara Institute of Science and Technology, RIKEN Center for Advanced Intelligence Project | Japan, Singapore | — |
| 17 | Robust point cloud registration framework based on deep graph matching | Fudan University, Shandong Academy of Sciences \| Qilu University of Technology | China | — |
| 18 | Regformer: An efficient projection-aware transformer network for large-scale point cloud registration | China University of Mining and Technology, ETH Zurich, Shanghai Jiao Tong University | China, Switzerland | **Influential** |
| 19 | Lepard: Learning partial point cloud matching in rigid and deformable scenes | The University of Tokyo | Japan | — |

| No. | Citing paper | Citing institution(s) | Country | S2 |
|---|---|---|---|---|
| 20 | Peal: Prior-embedded explicit attention learning for low-overlap point cloud registration | Hangzhou Dianzi University, Shanghai Jiao Tong University, Zhejiang Gongshang University | China | Influential |
| 21 | Frame averaging for invariant and equivariant network design | Facebook AI Research, McGill University, Meta AI | Canada, United States | — |
| 22 | Unsupervised deep probabilistic approach for partial point cloud registration | ETH Zurich, Fondazione Bruno Kessler, Peking University | China, Italy, Switzerland | — |
| 23 | Back to the feature: classical 3d features are (almost) all you need for 3d anomaly detection | Hebrew University of Jerusalem, The Hebrew University of Jerusalem | Israel | — |
| 24 | Freeze: Training-free zero-shot 6d pose estimation with geometric and vision foundation models | Fondazione Bruno Kessler, University of Trento | Italy | — |
| 25 | Turboreg: Turboclique for robust and efficient point cloud registration | Beijing Polytechnic, State Key Laboratory of Information Engineering in Surveying Mapping and Remote Sensing, University of Zaragoza | China | — |
| 26 | PANet: A point-attention based multi-scale feature fusion network for point cloud registration | Xidian University | China | — |
| 27 | Fastmac: Stochastic spectral sampling of correspondence graph | Peking University, Shanghai AI Lab, Shanghai Jiao Tong University | China, United States | — |
| 28 | Dual focus-attention transformer for robust point cloud registration | Fudan University, Qilu University of Technology \| Shandong Academy of Sciences, Shandong Academy of Sciences \| Qilu University of Technology | China, People's Republic of China | — |
| 29 | Riga: Rotation-invariant and globally-aware descriptors for point cloud registration | National University of Defense Technology, Shanghai Jiao Tong University, Technical University of Munich | China, Germany | Influential |
| 30 | Colorpcr: Color point cloud registration with multi-stage geometric-color fusion | Shanghai AI Laboratory, Tsinghua University, Xi'an Jiaotong University | China | — |

**Showing the 30 most-cited of 436 independent citing papers.**

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**

## GrowSP: Unsupervised Semantic Segmentation of 3D Point Clouds

2023 · 105 citations (GS)

Field-normalised: 64 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2023 indexed by Semantic Scholar, by citation count.

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

## Contribution 2

**Claim — Contribution 2**

*The researcher pioneered general radiance fields for 3D representation, subsequently extending this framework to dynamic physics learning and scene geometry decomposition.*

The researcher established a foundational approach to 3D representation and rendering through the seminal 2021 paper 'GRF: Learning a General Radiance Field for 3D Representation and Rendering.' This core work serves as the anchor for a sustained line of inquiry into neural scene representations.

This line of work appears to address the challenge of generalizing 3D scene understanding beyond static geometry. The titles of subsequent publications suggest a logical progression from general radiance fields to more complex domains. Specifically, the 2023 paper 'NVFi: Neural Velocity Fields for 3D Physics Learning from Dynamic Videos' indicates an expansion into dynamic physical phenomena, while 'DM-NeRF: 3D Scene Geometry Decomposition and Manipulation from 2D Images' suggests advancements in structural analysis and manipulation capabilities.

The significance of this contribution is evidenced by substantial academic uptake. The core paper has accumulated 420 citations, while the follow-up works have garnered 36 and 99 citations respectively. Crucially, analysis of citing literature reveals that 93.3% of citations originate from independent researchers, demonstrating that this framework has been widely adopted and built upon by the broader scientific community rather than solely by the researcher's immediate collaborators.

**INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 328** · **12 flagged influential by Semantic Scholar**

**CORE PAPER**

### GRF: Learning a General Radiance Field for 3D Representation and Rendering

2021 · 420 citations (GS)

Field-normalised: 257 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2021 indexed by Semantic Scholar, by citation count.

| No. | Citing paper | Citing institution(s) | Country | S2 |
|---|---|---|---|---|
| 1 | Enhance-NeRF: Multiple Performance Evaluation for Neural Radiance Fields | Nanjing Agricultural University, Nanjing University of Information Science and Technology | China | — |
| 2 | Advances in feed-forward 3d reconstruction and view synthesis: A survey | Caltech, Harvard University, Hillbot | China, Germany, Singapore | — |
| 3 | Zerorf: Fast sparse view 360deg reconstruction with zero pretraining | UC San Diego, University of California San Diego | United States | — |
| 4 | Neural fields in visual computing and beyond | Brown University, Google, Massachusetts Institute of Technology | Canada, Israel, United States | — |
| 5 | Neural rays for occlusion-aware image-based rendering | Max Planck Institute for Informatics, Texas A&M University, The University of Hong Kong | China, Germany, Hong Kong | — |
| 6 | Nerf-sr: High quality neural radiance fields using supersampling | Kuaishou Technology, Tsinghua University, University of Pennsylvania | China, United States | — |

| No. | Citing paper | Citing institution(s) | Country | S2 |
|---|---|---|---|---|
| 7 | Nope-nerf: Optimising neural radiance field with no pose prior | Mohammed Bin Zayed University of Artificial Intelligence, University of Oxford | United Arab Emirates, United Kingdom | — |
| 8 | Mine: Towards continuous depth mpi with nerf for novel view synthesis | ByteDance, Fudan University, National University of Singapore | China, Singapore | — |
| 9 | Multi-view consistent generative adversarial networks for 3d-aware image synthesis | DAMO Academy, Alibaba Group, National University of Singapore, University of Technology Sydney | Australia, China, Singapore | — |
| 10 | Multi-view consistent generative adversarial networks for compositional 3d-aware image synthesis | DAMO Academy, Alibaba Group, National University of Singapore, University of Technology Sydney | Australia, Singapore, United States | — |
| 11 | Flowcam: Training generalizable 3d radiance fields without camera poses via pixel-aligned scene flow | Harvard University, Massachusetts Institute of Technology, Stanford University | United States | — |
| 12 | I-DACS: Always maintaining consistency between poses and the field for radiance field construction without pose prior | Tongji University, University of Macau | China | — |
| 13 | 3D hierarchical refinement and augmentation for unsupervised learning of depth and pose from monocular video | Shanghai Jiao Tong University | China | — |
| 14 | Mononerf: Learning generalizable nerfs from monocular videos without camera poses | Meta AI, UC San Diego, University of California, Irvine Medical Center | United States | — |
| 15 | pixelsplat: 3d gaussian splats from image pairs for scalable generalizable 3d reconstruction | Massachusetts Institute of Technology, Simon Fraser University | Canada, United States | — |
| 16 | Tensorf: Tensorial radiance fields | Adobe Research, ShanghaiTech University, University of California San Diego | China, Germany, United States | — |
| 17 | Dl3dv-10k: A large-scale scene dataset for deep learning-based 3d vision | Adobe Inc., Google Inc., Purdue University | United States | — |
| 18 | Reconfusion: 3d reconstruction with diffusion priors | Columbia University, Google, Google DeepMind | United Kingdom, United States | — |
| 19 | Plenoctrees for real-time rendering of neural radiance fields | UC Berkeley, University of California, Irvine Medical Center | United States | — |
| 20 | Generative novel view synthesis with 3d-aware diffusion models | NVIDIA, Stanford University | United States | — |
| 21 | Ibrnet: Learning multi-view image-based rendering | Cornell University, Google DeepMind, Google Research | United Kingdom, United States | — |
| 22 | Kilonerf: Speeding up neural radiance fields with thousands of tiny mlps | ETH Zurich, Max Planck Institute for Intelligent Systems, Universität Tübingen | China, Germany, Switzerland | — |
| 23 | Mvimgnet: A large-scale dataset of multi-view images | ByteDance, Sun Yat-sen University, The Chinese University of Hong Kong, Shenzhen | China | — |

| No. | Citing paper | Citing institution(s) | Country | S2 |
|---|---|---|---|---|
| 24 | Advances in neural rendering | Google Inc., Google Research, Massachusetts Institute of Technology | Germany, United States | — |
| 25 | Wonderworld: Interactive 3d scene generation from a single image | Cornell Tech, MIT, Stanford University | United States | — |
| 26 | Urban radiance fields | Google, Google Research, University of Toronto | Canada, United States | — |
| 27 | Multidiff: Consistent novel view synthesis from a single image | Max Planck Society, Meta, Technical University of Munich | Germany, Switzerland | — |
| 28 | Diffusion with forward models: Solving stochastic inverse problems without direct supervision | Massachusetts Institute of Technology, Princeton University | United States | — |
| 29 | DONeRF: Towards real-time rendering of compact neural radiance fields using depth oracle networks | Facebook, Graz University of Technology | Austria, United States | — |
| 30 | Nex: Real-time view synthesis with neural basis expansion | VISTEC | Thailand | — |

**Showing the 30 most-cited of 328 independent citing papers.**

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

**NVFi: Neural Velocity Fields for 3D Physics Learning from Dynamic Videos**

2023 · 36 citations (GS)

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

FOLLOW-UP WORK

**DM-NeRF: 3D Scene Geometry Decomposition and Manipulation from 2D Images**

2023 · 99 citations (GS)

Field-normalised: 86 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2023 indexed by Semantic Scholar, by citation count.

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

## Contribution 3

### Claim — Contribution 3

*The researcher pioneered adversarial learning for single-view 3D reconstruction, establishing a foundational framework that subsequent work extended to dense reconstruction and non-rigid physical dynamics.*

The researcher established a seminal contribution in 3D computer vision through the 2017 paper '3D Object Reconstruction from a Single Depth View with Adversarial Learning.' This core work introduced a novel approach to reconstructing three-dimensional objects from limited depth data, leveraging adversarial learning techniques to enhance reconstruction quality and realism.

This line of work appears to address the challenge of generating complete 3D models from sparse or single-view inputs. The originality lies in applying adversarial training to this specific reconstruction problem. The researcher subsequently expanded this foundation in 2018 with 'Dense 3D Object Reconstruction from a Single Depth View,' suggesting an evolution toward higher-fidelity outputs. Additionally, the 2018 paper '3D-PhysNet' indicates a broadening of scope to incorporate intuitive physics for non-rigid deformations, demonstrating the versatility of the initial methodological framework.

The significance of this contribution is evidenced by substantial academic uptake. The core 2017 paper has accumulated 246 citations, while the 2018 dense reconstruction follow-up has garnered 205 citations. With 93.3% of the researcher's total classified citations originating from independent researchers, this indicates that the community widely recognizes and builds upon this specific line of inquiry, validating its impact beyond the researcher's immediate circle.

**INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 70** · **6 flagged influential by Semantic Scholar**

**CORE PAPER**

### 3D Object Reconstruction from a Single Depth View with Adversarial Learning

2017 · 246 citations (GS)

Field-normalised: 206 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2017 indexed by Semantic Scholar, by citation count.

| No. | Citing paper | Citing institution(s) | Country | S2 |
|---|---|---|---|---|
| 1 | Image synthesis with adversarial networks: A comprehensive survey and case studies | École de Technologie Supérieure, Massey University, Shanghai Jiao Tong University | Canada, China, New Zealand | — |
| 2 | Softpool++: An encoder–decoder network for point cloud completion | Google, Technical University of Munich, Technische Universität München | Germany, Switzerland | **Influential** |
| 3 | Reverse2complete: Unpaired multimodal point cloud completion via guided diffusion | Lancaster University, University of Science and Technology of China | China, United Kingdom | — |
| 4 | 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 | — |
| 5 | Artificial intelligence in the creative industries: a review | University of Bristol | United Kingdom | — |
| 6 | Pu-gan: a point cloud upsampling adversarial network | Huazhong University of Science and Technology, Hunan University, Tel Aviv University | China, Israel | — |
| 7 | GAN-based generation of realistic 3D volumetric data: A systematic review and taxonomy | University Medicine Essen, University Medicine Essen; Graz University of Technology, University of Minho | Germany, Germany; Austria, Portugal | — |
| 8 | PUFA-GAN: A frequency-aware generative adversarial network for 3D point cloud upsampling | City University of Hong Kong, De Montfort University, Peking University | China, United Kingdom | — |
| 9 | Escaping plato's cave: 3d shape from adversarial rendering | Google, University College London | United Kingdom, United States | — |
| 10 | A survey of image synthesis and editing with generative adversarial networks | Tsinghua University, University of Bath | China, United Kingdom | — |

| No. | Citing paper | Citing institution(s) | Country | S2 |
|---|---|---|---|---|
| 11 | Convolutional generation of textured 3d meshes | ETH Zurich, KU Leuven | Belgium, Switzerland | — |
| 12 | Unsupervised point cloud representation learning with deep neural networks: A survey | Nanyang Technological University, Wenzhou University | China, Singapore | — |
| 13 | Towards point cloud completion: Point rank sampling and cross-cascade graph cnn | China University of Petroleum, Peking University | China | — |
| 14 | Dso: Aligning 3d generators with simulation feedback for physical soundness | Nanyang Technological University, University of Oxford | United Kingdom | — |
| 15 | Amodal3r: Amodal 3d reconstruction from occluded 2d images | Nanyang Technological University, Singapore Institute of Technology, University of Cambridge | Singapore, United Kingdom | — |
| 16 | Advancements in point cloud data augmentation for deep learning: A survey | Xi'an Jiaotong-Liverpool University | China | — |
| 17 | Pointr: Diverse point cloud completion with geometry-aware transformers | Tsinghua University | China | — |
| 18 | Learning local displacements for point cloud completion | Google, Technical University of Munich, Technische Universität München | Germany, Switzerland | — |
| 19 | FinerPCN: High fidelity point cloud completion network using pointwise convolution | Xidian University | China | — |
| 20 | Point cloud completion via relative point position encoding and regional attention | Huazhong University of Science and Technology | China | — |
| 21 | CompleteDT: Point cloud completion with information-perception transformers | Beijing Institute of Optoelectronic Technology, Beijing Institute of Technology | China | — |
| 22 | Human body shape completion with implicit shape and flow learning | Centre Inria de l'Université Grenoble Alpes, Tsinghua University | China, France | — |
| 23 | MIX-NET: Deep learning-based point cloud processing method for segmentation and occlusion leaf restoration of seedlings | Agricultural Genomics Institute at Shenzhen, Ministry of Education of the People's Republic of China, Nanjing Normal University | China | — |
| 24 | SDA-Net: A global feature point cloud completion network based on serialization and dual attention | China University of Geosciences | China | — |
| 25 | Mendnet: Restoration of fractured shapes using learned occupancy functions | Clarkson University | United States | — |
| 26 | Structure-aware completion of plant 3D LiDAR point clouds via a multi-resolution GAN-inversion network | Bureau of Agriculture and Rural Affairs, China Agricultural University, Nanjing Institute of Agricultural Mechanization | China | — |

| No. | Citing paper | Citing institution(s) | Country | S2 |
|---|---|---|---|---|
| 27 | RefComp: A Reference-guided Unified Framework for Unpaired Point Cloud Completion | ETH Zurich, Southern University of Science and Technology, SUSTech | China, Switzerland, United Kingdom | — |
| 28 | FEPoinTr: Point cloud completion networks independent of batch size | Guilin University of Electronic Technology, Guilin University of Technology | China | — |
| 29 | Implicit geometric regularization for learning shapes | Weizmann Institute of Science | Israel | — |
| 30 | Behave: Dataset and method for tracking human object interactions | Google Research, Max Planck Institute for Informatics, Tübingen AI Center | Germany, United States | — |

**Showing the 30 most-cited of 70 independent citing papers.**

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

### 3D-PhysNet: Learning the Intuitive Physics of Non-Rigid Object Deformations

2018 · 41 citations (GS)

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

FOLLOW-UP WORK

### Dense 3D Object Reconstruction from a Single Depth View

2018 · 205 citations (GS)

Field-normalised: 131 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2018 indexed by Semantic Scholar, by citation count.

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

## D. Citing-Institution Prestige & Geography

### Top citing institutions

| Institution | Country | World ranking | Citing papers |
|---|---|---|---|
| Tsinghua University | China | SCImago #8 · THE 12 · QS =17 | 102 |
| Nanyang Technological University | Singapore | SCImago #137 | 97 |
| Wuhan University | PR China | SCImago #80 · THE =122 · QS 186 | 89 |
| Shanghai Jiao Tong University | China | SCImago #10 · THE 40 · QS =47 | 78 |
| Zhejiang University | China | SCImago #6 · THE 39 · QS 49 | 74 |
| Sun Yat-sen University | China | SCImago #40 · THE 201–250 · QS =276 | 64 |
| University of Oxford | United Kingdom | SCImago #26 · THE 1 · QS 4 | 62 |
| Chinese Academy of Sciences | China | SCImago #2 | 58 |

| Institution | Country | World ranking | Citing papers |
|---|---|---|---|
| Xiamen University | China | SCImago #275 · THE 251–300 · QS 341 | 56 |
| Peking University | China | SCImago #11 · THE 13 · QS 14 | 53 |
| National University of Singapore | Singapore | SCImago #59 · THE 17 · QS 8 | 48 |
| The Chinese University of Hong Kong | Hong Kong | SCImago #163 · THE =41 · QS =32 | 46 |
| Stanford University | United States | SCImago #18 · THE =5 · QS 3 | 45 |
| The Hong Kong Polytechnic University | Hong Kong | SCImago #256 · THE 80 · QS 54 | 42 |
| National University of Defense Technology | China | SCImago #488 | 41 |

### Geographic distribution of citing authors

| Country | Citing papers |
|---|---|
| China | 1,402 |
| United States | 429 |
| United Kingdom | 174 |
| Germany | 151 |
| Singapore | 146 |
| Hong Kong | 127 |
| Canada | 87 |
| Australia | 87 |
| South Korea | 67 |
| Switzerland | 64 |
| France | 47 |
| Italy | 34 |

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 | RandLA-Net: Efficient Semantic Segmentation of Large-Scale Point Clouds | 1,244 | Dhanasar — Prong 2 (well-positioned) |
| Contribution 2 | GRF: Learning a General Radiance Field for 3D Representation and Rendering | 328 | Dhanasar — Prong 2 (well-positioned) |
| Contribution 3 | 3D Object Reconstruction from a Single Depth View with Adversarial Learning | 70 | Dhanasar — Prong 2 (well-positioned) |