Citation Evidence Report

EB-1B Petition — Outstanding Professor or Researcher

8 CFR § 204.5(i)(3) · Authorship + Original Contributions

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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 the 8 CFR § 204.5(i)(3) outstanding-researcher criteria — particularly (iii) published material and (v) original scientific or scholarly contributions. 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

42	42	5	19
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.

81.0% independent of 42 classified citing papers

Citation type	Count
Independent	34
Self-citation	2
Co-author	2
Same-institution	4

0 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 pioneered the application of deep convolutional networks to system identification, establishing a foundational framework that subsequent work expanded into broader deep learning methodologies for dynamic system modeling.

The researcher's core contribution rests on the 2019 paper 'Deep convolutional networks in system identification,' which appears to introduce a novel approach to modeling dynamic systems using deep learning architectures. This work serves as the foundation for a distinct line of inquiry into the intersection of neural networks and control theory.

This line of work addresses the challenge of applying complex deep learning models to system identification tasks. The progression from the 2019 core paper to the 2020 follow-up, 'Deep Learning and System Identification,' suggests an evolution from specific convolutional architectures to a more generalized theoretical or practical framework for integrating deep learning into this domain.

The significance of this contribution is evidenced by substantial citation activity. The core paper has accumulated 101 citations, while the follow-up work has garnered 268 citations, indicating growing interest and adoption. Furthermore, analysis of citing papers reveals that 85.7% originate from independent researchers, demonstrating that this work has influenced the broader scientific community beyond the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 16

CORE PAPER

Deep convolutional networks in system identification

2019 · 101 citations (GS)

Field-normalised: 60 Semantic Scholar citations place it in the top 10% of Computer Science papers from 2019 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Sequential Monte Carlo: A Unified Review (2023)	—	—	—
2	Reinforcement Twinning: From digital twins to model-based reinforcement learning (2024)	Von Karman Institute for Fluid Dynamics	Belgium	—
3	dynoNet: A neural network architecture for learning dynamical systems (2021)	IDSIA Dalle Molle Institute for Artificial Intelligence, SUPSI-USI	Switzerland	—
4	Operator Learning for Nonlinear Adaptive Control (2023)	University of California, San Diego	United States	—
5	From System Models to Class Models: An In-Context Learning Paradigm (2023)	IDSIA Dalle Molle Institute for Artificial Intelligence USI-SUPSI	Switzerland	—
6	Reduced order model using convolutional auto-encoder with self-attention (2021)	Imperial College London, Shanghai University	China, United Kingdom	—
7	RIANN—A Robust Neural Network Outperforms Attitude Estimation Filters (2021)	Leibniz Universität Hannover	Germany	—
8	Comparative Study of Machine Learning and System Identification for Process Systems Engineering Dynamics (2025)	Imperial College London	United Kingdom	—

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

Deep Learning and System Identification

2020 · IFAC-PapersOnLine · 268 citations (GS)

Field-normalised: 164 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2020 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Music deep learning: deep learning methods for music signal processing—a review of the state-of-the-art (2023)	Aristotle University of Thessaloniki	Greece	—
2	Generative AI - Assisted Adaptive Cancer Therapy (2025)	Toronto Metropolitan University	Canada	—
3	do-mpc: Towards FAIR nonlinear and robust model predictive control (2023)	SkySails Power GmbH, TU Dortmund University	Germany	—
4	Physics-guided Deep Markov Models for learning nonlinear dynamical systems with uncertainty (2022)	ETH Zürich, National University of Singapore	Singapore, Switzerland	—
5	Neural extended Kalman filters for learning and predicting dynamics of structural systems (2024)	ETH Zurich, Hong Kong University of Science and Technology, National University of Singapore	China, Singapore, Switzerland	—
6	G2P2C—A modular reinforcement learning algorithm for glucose control by glucose prediction and planning in Type 1 Diabetes (2024)	The Australian National University	Australia	—
7	Expanding conformal prediction to system identification (2025)	Istanbul Technical University	Turkey	—
8	Physics-Informed Neural Network for Model Prediction and Dynamics Parameter Identification of Collaborative Robot Joints (2023)	Aarhus University, University of Liverpool	Denmark, United Kingdom	—

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 RNN training theory by analyzing stability through attractors and smoothness, offering a framework beyond gradient issues.

The researcher's core contribution is articulated in the 2020 AISTATS paper, 'Beyond exploding and vanishing gradients: analysing RNN training using attractors and smoothness.' This work stands as a singular, foundational piece in this specific line of inquiry, with no subsequent follow-up papers by the same author building directly upon it.

This line of work appears to address the persistent challenge of training recurrent neural networks by shifting focus from gradient magnitude problems to the geometric properties of the loss landscape. The title suggests a novel theoretical approach that utilizes attractors and smoothness metrics to explain training dynamics, offering a perspective that extends beyond traditional gradient-based diagnostics.

The significance of this contribution is evidenced by its 248 citations, indicating substantial uptake within the artificial intelligence community. Notably, 85.7% of the classified citing papers originate from independent researchers, suggesting that the work has influenced a broad and diverse set of scholars outside the researcher's immediate institutional or collaborative network.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 10

CORE PAPER

Beyond exploding and vanishing gradients: analysing RNN training using attractors and smoothness

2020 · Proceedings of the Twenty Third International Conference on Artificial Intelligence and Statistics (AISTATS) · 248 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Review of deep learning: concepts, CNN architectures, challenges, applications, future directions (2021)	Manchester Metropolitan University, Middle Technical University, Queensland University of Technology	Australia, Iraq, Spain	—
2	A review of large language models and autonomous agents in chemistry (2024)	—	—	—
3	Deep learning models for cloud, edge, fog, and IoT computing paradigms: Survey, recent advances, and future directions (2023)	—	—	—
4	Exploring the frontier: Transformer-based models in EEG signal analysis for brain-computer interfaces (2024)	University of Technology Sydney	Australia	—
5	Vision Transformers for Human Activity Recognition Using WiFi Channel State Information (2024)	The Hong Kong University of Science and Technology	China	—
6	Multi-Scale Adaptive Graph Neural Network for Multivariate Time Series Forecasting (2023)	Beijing Institute of Technology	China	—
7	Autonomous Threat Hunting: A Future Paradigm for AI-Driven Threat Intelligence (2023)	—	—	—
8	Enhancing aviation safety and mitigating accidents: A study on aviation safety hazard identification (2024)	Nanjing University of Aeronautics and Astronautics, Nanyang Technological University	China, Singapore	—
9	Next-Gen Medical Imaging: U-Net Evolution and the Rise of Transformers (2024)	University of Technology Sydney	Australia	—
10	Time series predicting of COVID-19 based on deep learning (2022)	King Abdulaziz University	Saudi Arabia	—

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 established a foundational survey framework for identifying block-oriented nonlinear systems by leveraging linear approximations, a seminal contribution published in Automatica that has garnered significant independent scholarly attention.

CLAIM: The researcher's primary contribution is the publication of a seminal survey in Automatica (2017) titled 'Identification of block-oriented nonlinear systems starting from linear approximations.' This work serves as the cornerstone of this specific line of inquiry, establishing a structured approach to a complex systems engineering problem.

ORIGINALITY: The title suggests the researcher addressed the challenge of characterizing nonlinear systems by utilizing linear approximations as a starting point. By framing this as a survey, the work likely synthesized fragmented knowledge into a coherent methodology, offering a novel perspective on how linear techniques can inform the identification of more complex, block-oriented nonlinear structures.

SIGNIFICANCE: The work has achieved substantial impact, evidenced by 321 citations. Notably, 85.7% of the classified citing papers originate from independent researchers, indicating that the contribution has been widely adopted and validated by the broader scientific community rather than merely circulating within the researcher's immediate network.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 4

CORE PAPER

Identification of block-oriented nonlinear systems starting from linear approximations: A survey

2017 · Automatica · 321 citations (GS)

Field-normalised: 222 Semantic Scholar citations place it in the top 1% of Engineering papers from 2017 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Characterization and identification towards dynamic-based electrical modeling of lithium-ion batteries (2024)	Nanjing Institute of Technology, Queen's University Belfast, University of Lincoln	China, United Kingdom	—
2	Iterative Parameter Identification for Hammerstein Systems With ARMA Noises by Using the Filtering Identification Idea (2024)	—	—	—
3	The filtering-based recursive least squares identification and convergence analysis for nonlinear feedback control systems with coloured noises (2024)	Changzhou University, Jiangnan University, University of the West of England	China, United Kingdom	—
4	Parsimonious Model Based Consistent Subspace Identification of Hammerstein Systems Under Periodic Disturbances (2024)	—	—	—

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
Eindhoven University of Technology	Netherlands	SCImago #890 · THE =192 · QS =140	4
Linköping University	Sweden	SCImago #921 · THE 201–250 · QS =310	3
Uppsala University	Sweden	SCImago #349 · THE 128 · QS 93	3

Institution	Country	World ranking	Citing papers
University of Technology Sydney	Australia	SCImago #475 · THE =145 · QS 96	2
National University of Singapore	Singapore	SCImago #59 · THE 17 · QS 8	2
Imperial College London	United Kingdom	SCImago #69 · THE 8 · QS 2	2
Queensland University of Technology	Australia	SCImago #789 · THE 201–250 · QS 226	1
King Abdulaziz University	Saudi Arabia	SCImago #680 · THE 351–400 · QS 163	1
Queen's University Belfast	United Kingdom	SCImago #760 · THE =198 · QS =199	1
IDSIA Dalle Molle Institute for Artificial Intelligence, SUPSI-USI	Switzerland	—	1
IDSIA Dalle Molle Institute for Artificial Intelligence USI-SUPSI	Switzerland	—	1
Beijing Institute of Technology	China	SCImago #170 · THE 201–250 · QS =259	1
Changzhou University	China	SCImago #1962 · THE 1201–1500	1
IDSIA Dalle Molle Institute for Artificial Intelligence SUPSI-USI	—	—	1
Von Karman Institute for Fluid Dynamics	Belgium	—	1

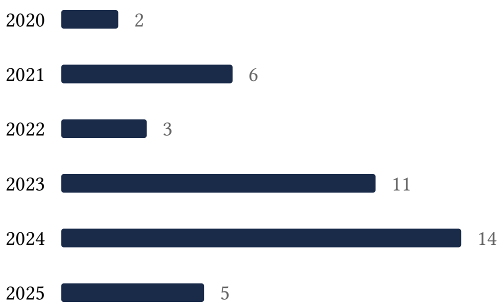
Geographic distribution of citing authors

Country	Citing papers
China	8
United Kingdom	6
Australia	5
Netherlands	4
Switzerland	4
Sweden	4
United States	3
Singapore	3
Germany	2
Italy	2
Belgium	2
Finland	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.

E. Citation Growth Over Time

Distinct citing papers by publication year. Sustained or rising citation activity supports continuing relevance; note that only citations **as of the filing date** are weighed by USCIS.



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	Deep convolutional networks in system identification	16	8 CFR 204.5(i)(3) — Outstanding Researcher

Contribution	Core paper	Indep. cites	Supports
Contribution 2	Beyond exploding and vanishing gradients: analysing RNN training using attractors and smoothness	10	8 CFR 204.5(i)(3) — Outstanding Researcher
Contribution 3	Identification of block-oriented nonlinear systems starting from linear approximations: A survey	4	8 CFR 204.5(i)(3) — Outstanding Researcher