Research Paper



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Research

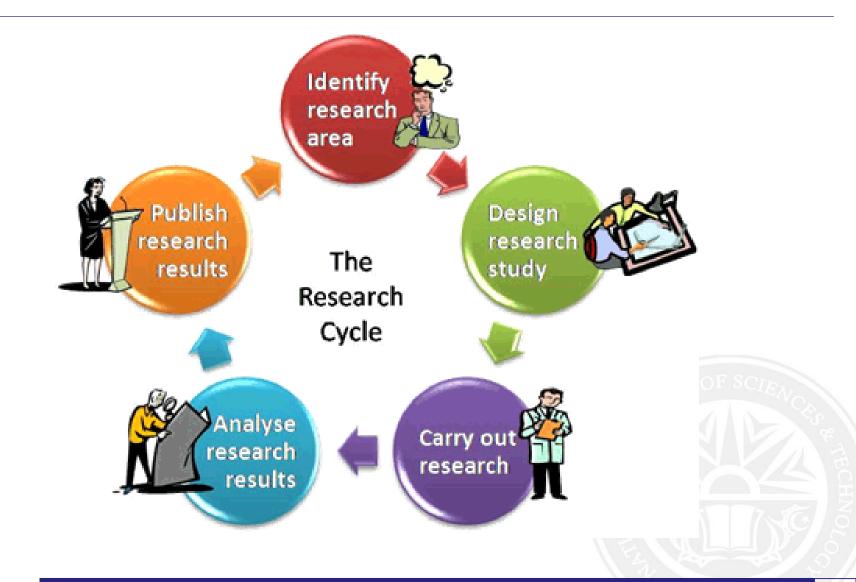
 Research is defined as the creation of new knowledge and/or the use of existing knowledge in a new and creative way so as to generate new concepts, methodologies and understandings.



Steps in conducting research

- Identification of research problem
- Literature review
- Specifying the purpose of research
- Determine specific research questions or hypotheses
- Data collection
- Analyzing and interpreting the data
- Reporting and evaluating research

Research cycle



How to Identify Research Problem?

Read, Read and Read!

Writing

Structure of Research Paper

- Title
- Abstract
- Introduction
- Related Work
- Problem Formulation
- Experimental/Methodology Section
- Results and Discussion
- Conclusions
- Acknowledgments
- References
- Supporting Information/ appendices



Research Paper-I

Title

As you craft a name for your paper, you should consider these potential objectives for the title you choose.

A title should:

- Describe the <u>content of the paper</u>
- <u>Distinguish the paper from others on a similar topic</u>
- <u>Catch</u> the reader's <u>attention</u> and interest
- Match search queries so people will find your paper (and cite it)

Research Paper-II

Abstract

150 – 250 wordsComprises of four parts

- Introduction/motivation/application
- Method
- Results
- Conclusion



Title

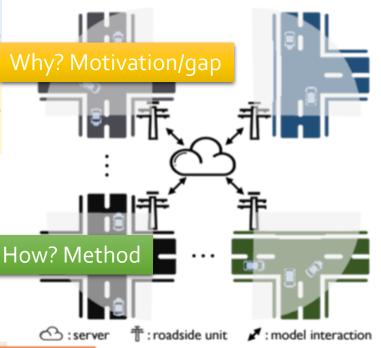
FedRSU: Federated Learning for Scene Flow Estimation on Roadside Units

Shaoheng Fang[†], Rui Ye[†], Wenhao Wang[†], Zuhong Liu, Yuxiao Wang, Yafei Wang Member, Siheng Chen Senior Member, Yanfeng Wang

What? introduction

Abstract—Roadside unit (KSU) can significantly improve the safety and robustness of autonomous vehicles through Vehicleto-Everything (V2X) communication. Currently, the usage of a single RSU mainly focuses on real-time inference and V2X collaboration, while neglecting the potential value of the highquality data collected by RSU sensors. Integrating the vast amounts of data from numerous RSUs can provide a rich source of data for model training. However, the absence of ground truth annotations and the difficulty of transmitting enormous volumes of data are two inevitable barriers to fully exploiting this hidden value. In this paper, we introduce FedRSU, an innovative federated learning framework for self-supervised scene flow estimation. In FedRSU, we present a recurrent selfsupervision training paradigm, where for each RSU, the scene flow prediction of points at every timestamp can be supervised by its subsequent future multi-modality observation. Another key component of FedRSU is federated learning, where multipl devices collaboratively train an ML model while keeping th training data local and private. With the power of the recurrent self-supervised learning paradigm, FL is able to leverage innumerable underutilized data from RSU. To verify the FedRSU framework, we construct a large-scale multi-modality dataset RSU-SF. The dataset consists of 17 RSU clients, covering various scenarios, modalities, and sensor settings. Based on RSU-SF, we show that FedRSU can greatly improve model performance in ITS and provide a comprehensive benchmark under diverse FL scenarios. To the best of our knowledge, we provide the first real-world LiDAR-camera multi-modal dataset and benchmark for the FL community.

Index Terms—Roadside unit, scene flow estimation, federated learning, self-supervised learning.



Results

U system overview, where multiple roadside units (RSUs) rain a scene flow estimation model without transmitting raw data under the coordination of a cloud server. Iteratively, each RSU trains a local model in a self-supervised manner, and the server aggregates local inficantly alleviate the challenges of tedious labeling single RSU.

arxiv.org/pdf/2401.12862.pdf

Research Paper-III

Don't use abbreviations or citations in the abstract. It should be able to stand alone without any footnotes.

Key words

- Use to search a paper
- Editor might use it to find reviewers
- Should be a part of abstract/title

Index Terms—Roadside unit, scene flow estimation, federated learning, self-supervised learning.

Introduction

Introduction of a paper comprises of following

- Motivation
- Application
- What, why and how you are doing?
- List of contribution/objective
- Paper organization



NOTE: Paragraphs should be linked/there should have continuity.

Research paper

Contribution

 Paper organization/ outline

ongoing advancements in both the fields of self-supervised scene flow learning and federated learning.

Overall, the key contributions of this work are as follows:

- We propose a new and practical federated learning framework on roadside units (FedRSU), where multiple RSUs collaboratively train a scene flow estimation model in a self-supervised manner.
- We propose a novel multi-modal scene flow learning method on each RSU client, which leverages image data to guide scene flow learning.
- We construct a diverse and practical scene flow dataset RSU-SF to promote the development of FedRSU and FL.
- We conduct extensive experiments on multiple baselines and scenarios to provide more insights and call for more future explorations.

Outline. This paper is structured as follows: In section II, we introduce related works. In Section III, we formulate the proposed setting, introduce the FedRSU framework, and our proposed federated multi-modal self-supervised learning algorithm. In Section IV, we introduce the constructed dataset RSU-SF for scene flow estimation and federated learning. In Section V, we conduct extensive experiments on diverse baselines and scenarios. In Section VI, we provide discussions on future directions and limitations. In Section VII, we summarize the paper.

FedRSU: Federated Learning for Scene Flow Estimation on Roadside Units

Shaoheng Fang[†], Rui Ye[†], Wenhao Wang[†], Zuhong Liu, Yuxiao Wang, Yafei Wang *Member*, Siheng Chen *Senior Member*, Yanfeng Wang

Introductory diagram

Abstract—Roadside unit (RSU) can significantly improve the safety and robustness of autonomous vehicles through Vehicleto-Everything (V2X) communication. Currently, the usage of a single RSU mainly focuses on real-time inference and V2X collaboration, while neglecting the potential value of the highquality data collected by RSU sensors. Integrating the vast amounts of data from numerous RSUs can provide a rich source of data for model training. However, the absence of ground truth annotations and the difficulty of transmitting enormous volumes of data are two inevitable barriers to fully exploiting this hidden value. In this paper, we introduce FedRSU, an innovative federated learning framework for self-supervised scene flow estimation. In FedRSU, we present a recurrent selfsupervision training paradigm, where for each RSU, the scene flow prediction of points at every timestamp can be supervised by its subsequent future multi-modality observation. Another key component of FedRSU is federated learning, where multiple devices collaboratively train an ML model while keeping the training data local and private. With the power of the recurrent self-supervised learning paradigm, FL is able to leverage innumerable underutilized data from RSU. To verify the FedRSU framework, we construct a large-scale multi-modality dataset RSU-SF. The dataset consists of 17 RSU clients, covering various scenarios, modalities, and sensor settings. Based on RSU-SF, we show that FedRSU can greatly improve model performance in ITS and provide a comprehensive benchmark under diverse FL scenarios. To the best of our knowledge, we provide the first real-world LiDAR-camera multi-modal dataset and benchmark for the FL community.

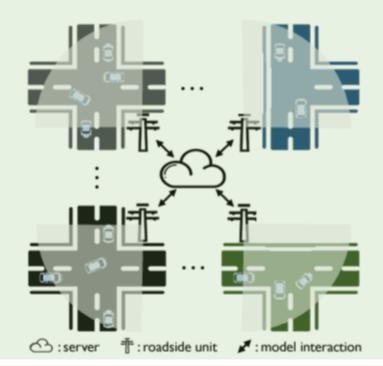


Fig. 1. FedRSU system overview, where multiple roadside units (RSUs) collaboratively train a scene flow estimation model without transmitting raw data under the coordination of a cloud server. Iteratively, each RSU trains a local model in a self-supervised manner, and the server aggregates local models. FedRSU can significantly alleviate the challenges of tedious labeling and limited data for one single RSU.

Index Terms—Roadside unit, scene flow estimati learning, self-supervised learning.



Which, when, where

Related work/literature review



- How to find papers? Which papers should be prefer to cite in a paper?
- How to read reference? How audience/readers' see the reference?
 - [1] A. Behl, D. Paschalidou, S. Donné, and A. Geiger. Point-flownet: Learning representations for rigid motion estimation from point clouds. In *CVPR*, 2019.
- How to write related work? Allow to answer an important question "NOVELTY!"

Related work/literature review

Theoretical table/ analysis (comparison)

Theoretical comparison among the characteristics of transition matrices with different methods.

References/ Technique	Reanalyze Data	Effected with sparsity of data	Temporal Time Dependent	GSs	Discrete level	Precise
[15] Baum-Welch	√	√	\checkmark	X	Х	X
[19] Multi-canonical Method	√	\checkmark	×	X	X	X
[13,14] Frequentist Approach	√	√ √	\checkmark	×	X	X
[20] Markov State Model	\checkmark	\checkmark	\checkmark	X	\checkmark	X
Proposed method	×	X	X	\checkmark	√	\checkmark

• Include 8-10 papers/methods (Good)

In this section, we formulate the problem of scene flow estimation, describe our novel design of multi-modal recurrent self-supervised learning for scene flow estimation at each RSU, and finally present the overall FedRSU system.

Problem formulation/maa. Problem Formulation

Introduction (mathematical) t

Nomenclature

Math symbol	Description				
$\tilde{X}, X^{(l)}$	Generalized States (GS) an f				
1	Ith times derivative				
X	Zero-order time derivativ				
	$X^{(0)}, n = 1$				
ν	First-order time derivativ				
	$X^{(1)}, n = 1$				
x	Zero-order time derivativ ⁸				
	$X^{(0)}, n=2$				
ν	First-order time derivativ				
	$X^{(1)}, n = 2$				
$\hat{\mathbf{x}}_{k+1 k}$	Prediction of next state				
$\mathbf{X}^{(l)}$	Coordinate system,				
	$[X^{(0)}, X^{(1)},, X^{(\mathcal{L})}]^{\tilde{T}}$				
$oldsymbol{\mu}_i^{(l)}$	Unit vector defining the o				
	tractor i				
P_i	Defines line of the attracti				
	i attractor f				
P_i^0	Defines the position vecto				
ı	traction P_i				
m_i	Position of <i>i</i> th attractor wl				
k	Time indexes				
••					

The focused task is scene flow estimation that describes the motion vector of points in 3D space, which is a crucial component to support various downstream tasks, including segmentation [19], instance segmentation [20], object detection [21], motion prediction [22], trajectory prediction [24], and more. To achieve this, our core goal is to train a scene flow estimation model on the constant stream of RSU data in a recurrent self-supervised paradigm. As is shown in Fig. 2, in the data stream of RSU sensors, the prediction at each frame can be supervised by its following future frame. Therefore, in our method, the denotation t can be any frame in the data stream.

Denote the dataset as $\mathcal{D} = \{(\mathbf{X}_i^{(pc)}, \mathbf{X}_i^{(img)})\}_{i=1}^N$, where N is the number of samples of the dataset. $\mathbf{X}_i^{(pc)} = (\mathbf{P}_i^{t-1}, \mathbf{P}_i^t)$, where source point cloud $\mathbf{P}_i^{t-1} = \{p_a^{t-1} \in \mathbb{R}^3\}_{a=1}^{n_1}$ and target point cloud $\mathbf{P}_i^t = \left\{p_b^t \in \mathbb{R}^3\right\}_{b=1}^{n_2}$ are from two consecutive time frames. $\mathbf{X}_i^{(pc)} = (\mathbf{I}_i^{t-1}, \mathbf{I}_i^t)$ are the corresponding images.

Basically, the objective of scene flow estimation is to estimate a motion vector $f_a \in \mathbb{R}^3$ of point $p_a^{t-1} \in \mathbb{R}^3$ from the first frame \mathbf{P}_{i}^{t-1} to its possible new position in the second frame \mathbf{P}_{i}^{t} . Due to the data sparsity of LiDAR point clouds and occlusion caused by moving objects, p_a may not have its corresponding point in \mathbf{P}_{i}^{t} and the point numbers n_{1} and n_{2} may differ. Therefore, the predicted flow $\mathbf{F}_i = \left\{f_a \in \mathbb{R}^3\right\}_{a=1}^{n_1}$ is not the point-to-point correspondences between \mathbf{P}_i^{t-1} and Pt. but the motion representation describing the scene.

Problem formulation/maa. Problem Formulation

Introduction (mathematical) t

III. FEDRSU: FEDERATED LEARNING ON RSUS

In this section, we formulate the problem of scene flow estimation, describe our novel design of multi-modal recurrent self-supervised learning for scene flow estimation at each RSU, and finally present the overall FedRSU system.

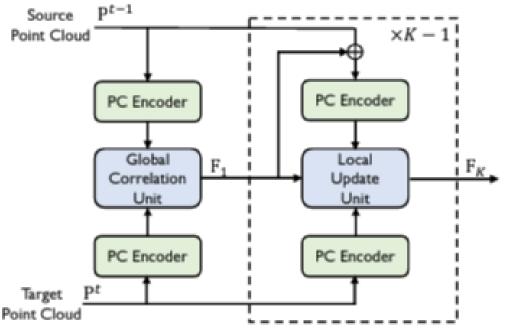
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<u>Methodology</u>

- Block diagram, table or
 - Try to avoid mathemat
 - Should be a generic dia



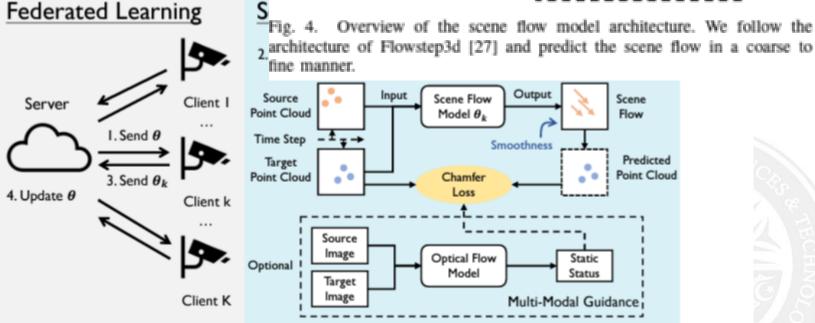


Fig. 3. Overview of FedRSU framework. FedRSU consists of four steps. 1) The server sends the global model to all available clients, 2) each client updates local model supervised by Chamfer loss and smoothness regularization, 3) each client sends local model to the server, 4) the server updates global model by aggregating received local models. These four steps will iterate for multiple rounds.

- Subsections: each sub section is linked with other, should be like story telling
- End of a sub-section provide an intro of the next subsection
- Every figure, table etc. should discussed/cited

Results and discussion

- Figure/results labelling, discussion should call each figure and provide discussion
- Position of figure/table in paper/report
- Discuss whatever you claim in your methodology/ introduction and related work section
- Prove it with figures and numbers
- Qualitive analysis vs quantitative analysis

Repeat the headings from your methodology!

Prove what you claim!

Results and discussion

- Comparison
 - With state of art method
 - Test your methodology with various <u>public datasets</u>
 - Provide <u>ablation study</u>
 - Quantitative comparison
- You don't necessarily have to include all the data you've gotten during the semester. This isn't your diary.
- Use appropriate methods of showing data. Don't try to manipulate the data to make it look like you did more than you actually did.

Conclusion and future work

- Should have continuity with your abstract
- Your conclusion is your chance to have the last word on the subject. The conclusion allows you to have the final say on the issues you have raised in your paper, to summarize your thoughts, to demonstrate the importance of your ideas, and to propel your reader to a new view of the subject. It is also your opportunity to make a good final impression and to end on a positive note.

References/ acknowledgement

• It is important to properly and appropriately cite references in scientific research papers in order to acknowledge your sources and give credit where credit is due.



Appendices

 Additional result, not much important but comprises of the interesting findings!

Experimental dataset

 Description of the dataset; whether its public dataset or not

How to start writing a paper?

Start with methodology

Then result and discussion

Observe the "conclusion"

And then write introduction and related work/literature review

Plagiarism

- Self-plagiarism
- Al generated content
- Plagiarism vs novelty

• How much plagiarism is allowed?



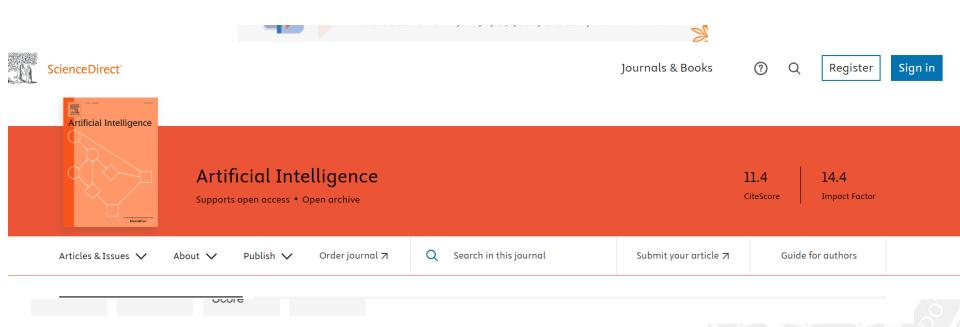
Research platform

- Researchgate (https://www.researchgate.net/)
- Google scholar (https://scholar.google.com/)
- Web of science (https://www.webofscience.com/)
- Scopus (https://www.scopus.com/)

etc.

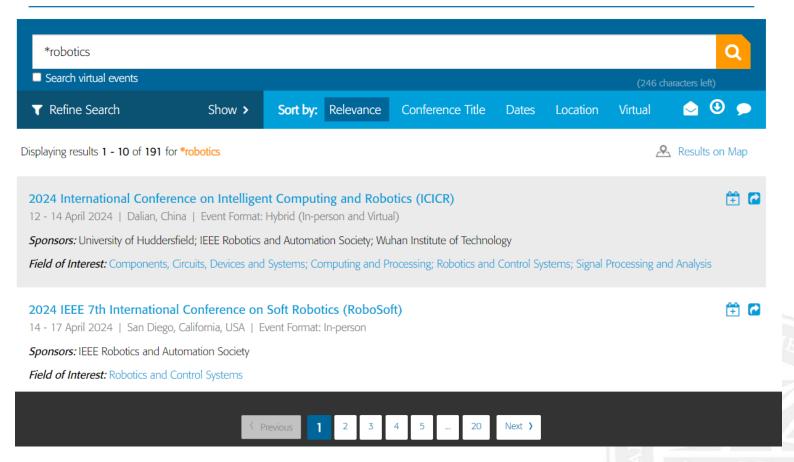
Ranking Matrices

- Hindex
- Impact factor
- Cite score (journal)
- Citation score (researchers) etc.



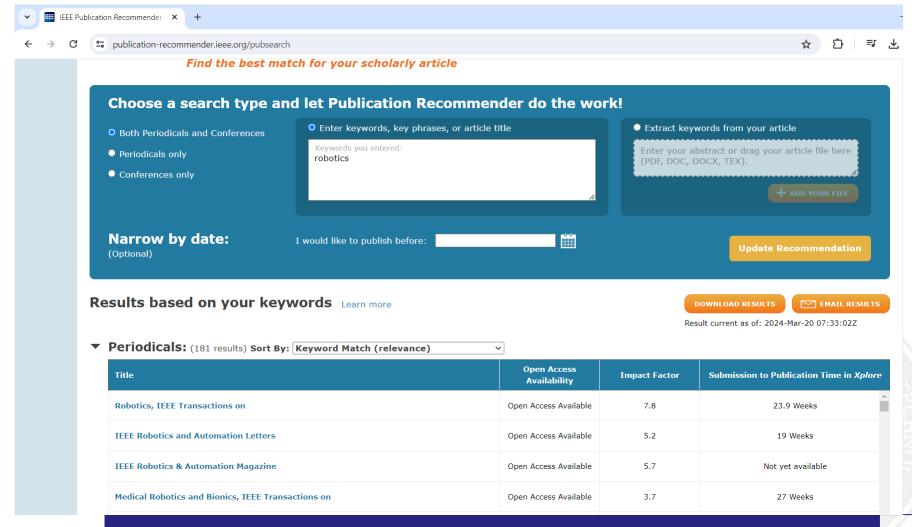
Submission/searching platform

IEEE Conference Search Results

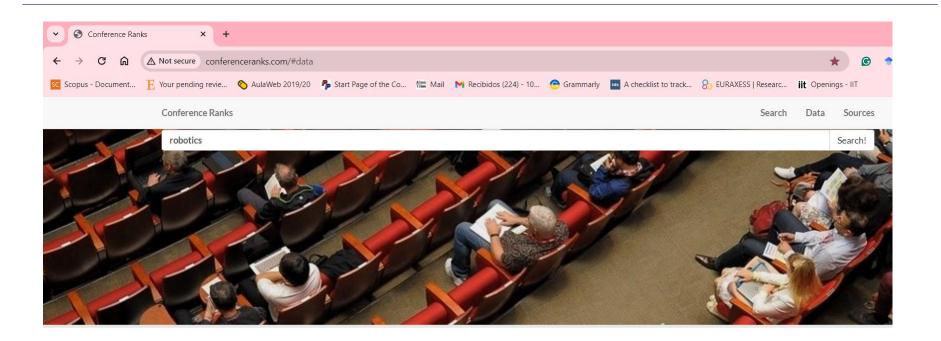


https://conferences.ieee.org/conferences_events/conferences/search?q=*&subsequent_q=&date=all&from=&to=®ion=all&country=all&pos=o&sortorder=desc&sponsor=&sponsor_type=all&state=all&field_of_interest=all&sortfield=relevance

https://publication-recommender.ieee.org/pubsearch



http://www.conferenceranks.com/#data

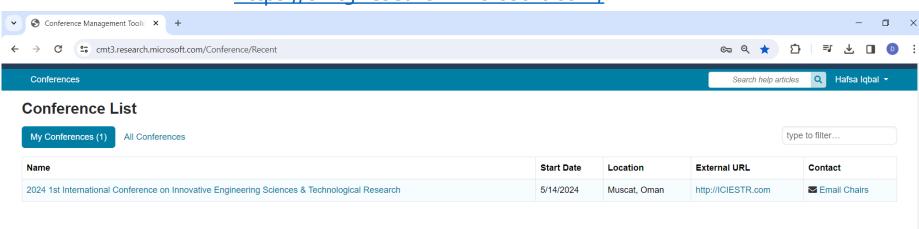


Conference Data

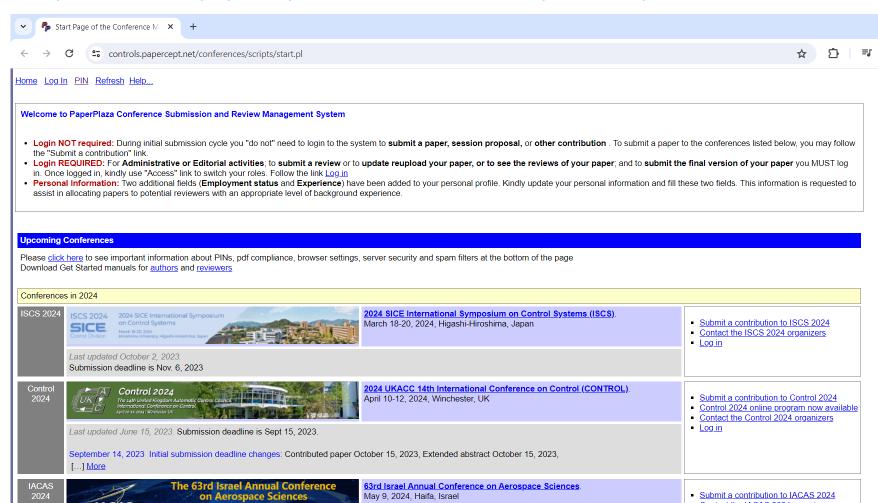
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Name	↓ Abbrv.	↓↑ Rank ↓	Source 11	
2008 International Conference on Biomedical Robotics and Biomechatronics	BIO ROB	В	ERA	
Australasian Conference on Robotics and Automation	ACRA	В	ERA	
Automation and Robotics International Symposium	ISARC	В	ERA	

Submission platform

https://cmt3.research.microsoft.com/



https://controls.papercept.net/conferences/scripts/start.pl



May 9, 2024, Haifa, Israel

9 May, 2024

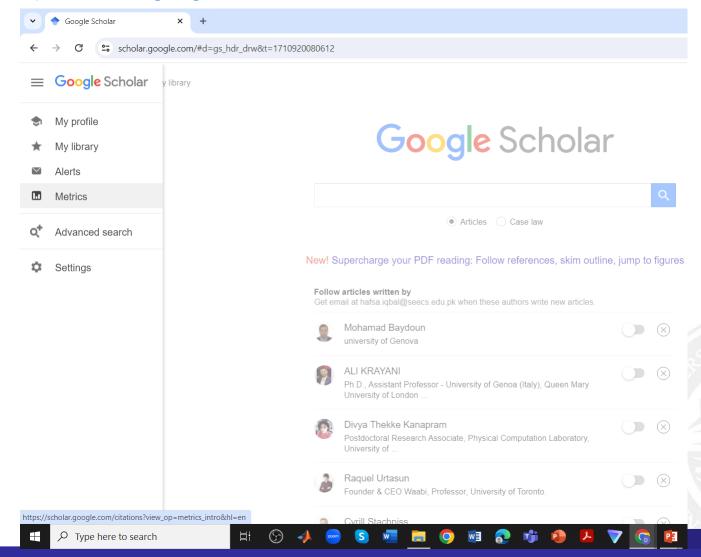
Submit a contribution to IACAS 2024

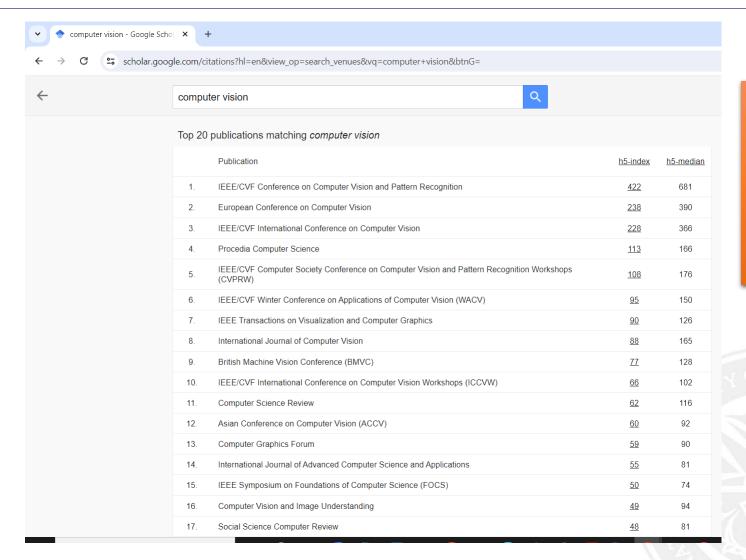
Contact the IACAS 2024 organizers

- Log in

Ranking Matrices

https://scholar.google.com/



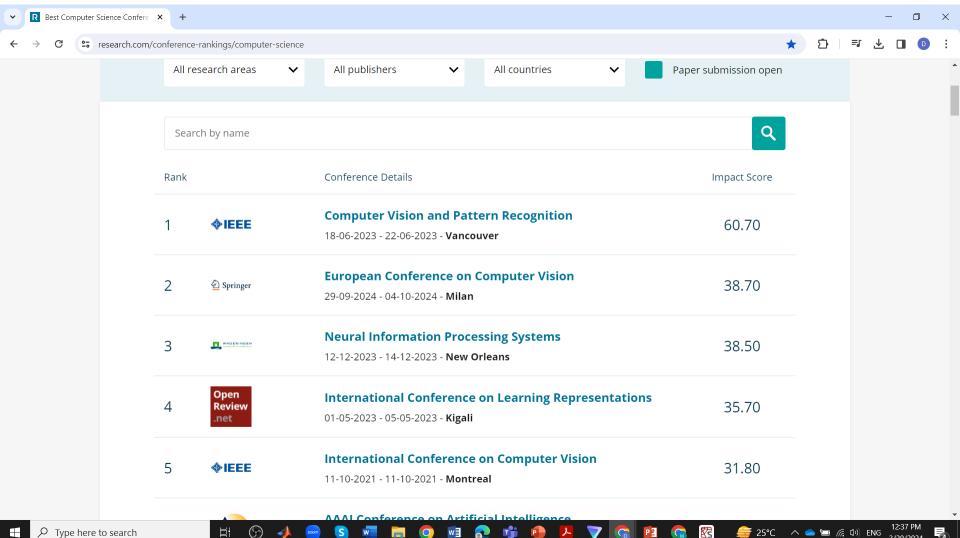


Quartiles

- Q1
- Q2
- Q₃
- Q4

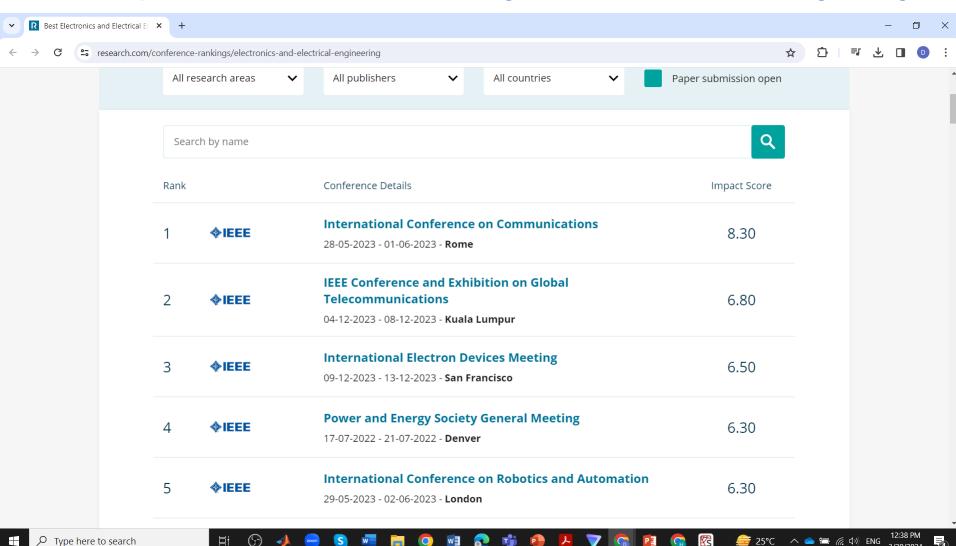
Best computer science conferences

https://research.com/conference-rankings/computer-science



Best Electrical and Electronics Conferences

https://research.com/conference-rankings/electronics-and-electrical-engineering



Steps to Publish in Conference



27th IEEE International Conference on Intelligent Transportation Systems September 24- 27, 2024 Edmonton, Canada

IEEE ITSC 2024



https://ieee-itsc.org/2024/

Submission Deadlines Extended

After multiple requests, the organization committee has decided to extend the submission. These **new deadlines are strict**, and no further extensions will be granted.

New Conference deadlines

April 08, 2024 April 22, 2024: Proposals due for invited sessions

April 15, 2024 May 01, 2024: Submission deadline for regular and invited session papers

May 30, 2024 June 07, 2024: Proposals due for workshops and tutorials

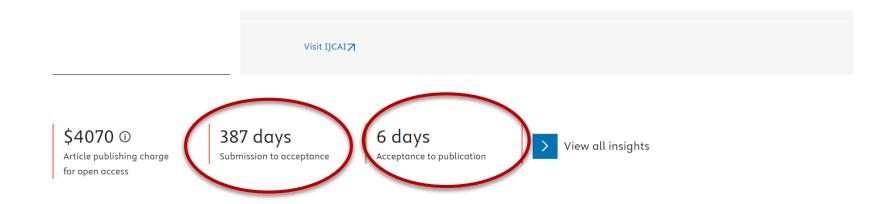
June 30, 2024 July 07, 2024: Decision notification

July 31, 2024: Final paper submission deadline

Invited session papers must be submitted via Papercept, using the code of the approved se with the approved proposers (to be shared with authors) before May 1st. Regular papers an submitted via Papercept.

Time to Publish in Journals

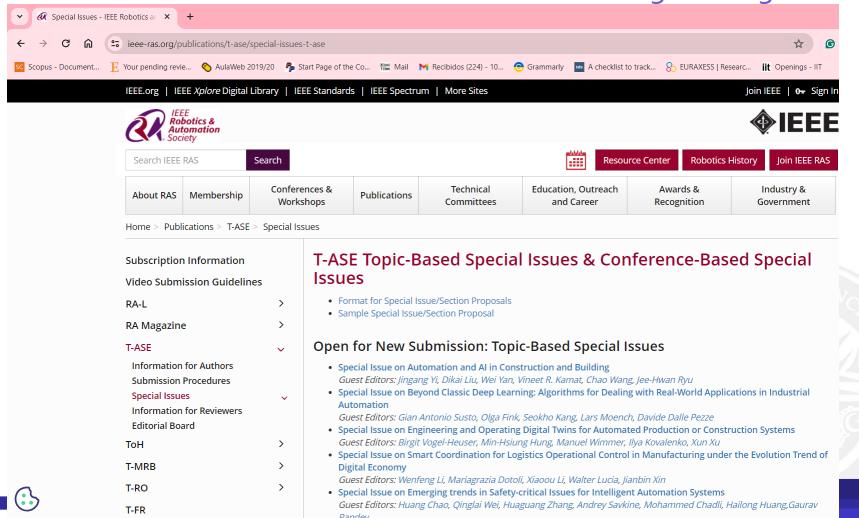
• https://www.sciencedirect.com/journal/artificial-intelligence



Special issues

https://www.ieee-ras.org/publications/t-ase/special-issues-t-ase

IEEE Transactions on Automation Science and Engineering



41

Platform

• Github

• LinkedIn

