Lecture Notes in Electrical Engineering 1436

Giuseppina Gini
Henk Nijmeijer
Dimitar Filev *Editors*

Informatics in Control, Automation and Robotics

20th International Conference, ICINCO 2023 Rome, Italy, November 13–15, 2023 Revised Selected Papers

Springer

Lecture Notes in Electrical Engineering

Volume 1436

The book series *Lecture Notes in Electrical Engineering* (LNEE) publishes the latest developments in Electrical Engineering—quickly, informally and in high quality. While original research reported in proceedings and monographs has traditionally formed the core of LNEE, we also encourage authors to submit books devoted to supporting student education and professional training in the various fields and applications areas of electrical engineering. The series cover classical and emerging topics concerning:

- Communication Engineering, Information Theory and Networks
- Electronics Engineering and Microelectronics
- Signal, Image and Speech Processing
- Wireless and Mobile Communication
- Circuits and Systems
- Energy Systems, Power Electronics and Electrical Machines
- Electro-optical Engineering
- Instrumentation Engineering
- Avionics Engineering
- Control Systems
- Internet-of-Things and Cybersecurity
- Biomedical Devices, MEMS and NEMS

For general information about this book series, comments or suggestions, please contact leontina.dicecco@springer.com.

To submit a proposal or request further information, please contact the Publishing Editor in your country:

China

Jasmine Dou, Editor (jasmine.dou@springer.com)

India, Japan, Rest of Asia

Swati Meherishi, Editorial Director (Swati.Meherishi@springer.com)

Southeast Asia, Australia, New Zealand

Ramesh Nath Premnath, Editor (ramesh.premnath@springernature.com)

USA, Canada

Michael Luby, Senior Editor (michael.luby@springer.com)

All other Countries

Leontina Di Cecco, Senior Editor (leontina.dicecco@springer.com)

**** This series is indexed by EI Compendex and Scopus databases. ****

Giuseppina Gini · Henk Nijmeijer · Dimitar Filev
Editors

Informatics in Control, Automation and Robotics

20th International Conference, ICINCO 2023 Rome, Italy, November 13–15, 2023 Revised Selected Papers

Springer

Editors
Giuseppina Gini
Politecnico di Milano
Milan, Italy

Henk Nijmeijer
Eindhoven University of Technology
Eindhoven, The Netherlands

Dimitar Filev
Research and Advanced Engineering
Ford Motor Company
Dearborn, MI, USA

ISSN 1876-1100 ISSN 1876-1119 (electronic)
Lecture Notes in Electrical Engineering
ISBN 978-3-031-94988-3 ISBN 978-3-031-94989-0 (eBook)
https://doi.org/10.1007/978-3-031-94989-0

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Organization

Conference Chair

Dimitar Filev, Ford Research/Texas A&M University, USA

Program Co-chairs

Giuseppina Gini, Politecnico di Milano, Italy
Henk Nijmeijer, Eindhoven University of Technology, The Netherlands

Program Committee

Hussein Abdullah, University of Guelph, Canada
El-Houssaine Aghezzaf, Ghent University, Faculty of Engineering and Architecture, Belgium
Eugenio Aguirre, University of Granada, Spain
Rudy Agustriyanto, University of Surabaya, Indonesia
Mojtaba Ahmadieh Khanesar, University of Nottingham, UK
Carlos Aldana, University of Guadalajara, Mexico
Manuel Aleixandre, Tokyo Institute of Technology, Japan
Joaquin Alvarez, Center Scientific Research Higher Education Ensenada Cicese, Mexico
Mihail Antchev, Technical University—Sofia, Bulgaria
Rui Araujo, University of Coimbra, Portugal
Mohd Ashraf Ahmad, University Malaysia Pahang, Malaysia
Ramiro Barbosa, ISEP/IPP—School of Engineering, Polytechnic Institute of Porto, Portugal

Michele Basso, University of Florence, Italy
Eric Baumgartner, Milwaukee School of Engineering, USA
Mahmoud Belhocine, CDTA, Algeria
Juri Belikov, Tallinn University of Technology, Estonia
Karsten Berns, University of Kaiserslautern-Landau, Germany
Sylvain Bertrand, ONERA—Université Paris-Saclay, France
Zafer Bingul, Kocaeli University, Turkey
Claudia-Adina Bojan-Dragos, Politehnica University of Timisoara, Romania
Magnus Boman, The Royal Institute of Technology, Sweden
Mohammad Bozorg, Yazd University, Iran, Islamic Republic of
Richard Braatz, Massachusetts Institute of Technology, USA
Laurent Burlion, Rutgers, the State University of New Jersey, USA
Simeon C. Calvert, TU Delft, The Netherlands
Kenneth Camilleri, University of Malta, Malta
Enrique Carrera, Army Polytechnic School Ecuador, Ecuador
Marco Castellani, University of Birmingham, UK
Paul Christodoulides, Cyprus University of Technology, Cyprus
Feng Chu, University of Evry Val d’Essonne, France
Marco Costanzo, Università degli Studi della Campania Luigi Vanvitelli, Italy
Michel Dambrine, Polytechnic University of Hauts-de-France, France
Paolo Di Giamberardino, Sapienza University of Rome, Italy
António Dourado, University of Coimbra, Portugal
Marc Ebner, Ernst-Moritz-Arndt-Universität Greifswald, Germany
Mehmet Önder Efe, Hacettepe University, Turkey
Ali Eydgahi, Eastern Michigan University, USA
Mohammed Fadali, UNR, USA
Baris Fidan, University of Waterloo, Canada
Paolo Fiorini, University of Verona, Italy
Thierry Fraichard, INRIA, France
Giuseppe Franzè, University of Calabria, Italy
Eduardo Oliveira Freire, Federal University of Sergipe, Brazil
Georg Frey, Automation and Energy Systems, Saarland University, Germany
Toyomi Fujita, Tohoku Institute of Technology, Japan
Andrej Gams, Jožef Stefan Institute, Slovenia
Péter Gáspár, SZTAKI, Hungary
Eduardo Godoy, São Paulo State University (UNESP), Brazil
Arthur Gómez, Universidade do Vale do Rio dos Sinos, Brazil
Juan-Jose Gonzalez De La Rosa, University of Cadiz, Spain
Corrado Guarino Lo Bianco, Università di Parma, Italy
Prof. Rajeev Gupta Rajasthan Technical University, India
Kensuke Harada, Osaka University, Japan
Khalifa Harib, UAE University, UAE
Hiroshi Hashimoto, Advanced Institute of Industrial Technology, Japan
Ramdane Hedjar, King Saud University, Saudi Arabia
Ghaleb Hoblos, Graduate School of Electrical Engineering, France

Wladyslaw Homenda, Warsaw University of Technology, Poland
Chiu-Fan Hsieh, National Formosa University, Taiwan, Republic of China
Liu Hsu, COPPE-UFRJ, Brazil
Daniela Iacoviello, Sapienza University of Rome, Italy
Junichi Iijima, Tokyo Institute of Technology, Japan
Gian Paolo Incremona, Politecnico di Milano, Italy
Gianluca Ippoliti, Università Politecnica delle Marche, Italy
Sarangapani Jagannathan, Missouri University of Science and Technology, USA
Isabel Jesus, ISEP/IPP—School of Engineering, Polytechnic Institute of Porto, Portugal
Fabrício Junqueira, University of São Paulo (USP), Brazil
Tohru Kawabe, University of Tsukuba, Japan
Balint Kiss, Budapest University of Technology and Economics, Hungary
Bahare Kiumarsi, Michigan State University, USA
Peter Košťál, Slovenská Technická Univerzita v Bratislave, Slovak Republic
Marek Kraft, Poznan University of Technology, Poland
Dragana Krstic, University of Nis, Faculty of Electronic Engineering, Serbia
Masao Kubo, National Defense Academy of Japan, Japan
Kolja Kühnlenz, Coburg University of Applied Sciences and Arts, Germany
Miroslav Kulich, Czech Technical University in Prague, Czech Republic
Sébastien Lahaye, Istia—LARIS, France
Ho-Hoon Lee, Southeastern Louisiana University, USA
Kauko Leiviskä, University of Oulu, Finland
Gordon Lightbody, University College Cork, Ireland
Antonio Lopes, University of Porto, Portugal
Anthony Maciejewski, Colorado State University, USA
Mohammad Javad Mahmoodabadi, Sirjan University of Technology, Iran, Islamic Republic of
Om Malik, University of Calgary, Canada
Federico Mari, University of Rome Foro Italico, Italy
Ester Martinez-Martin, University of Alicante, Spain
Jorge Martins, Instituto Superior Técnico, Portugal
Lorinc Marton, Sapientia Hungarian University of Transylvania, Romania
Pavlo Maruschak, Ternopil National Ivan Puluj Technical University, Ukraine
Luca Mazzola, HSLU—Lucerne University of Applied Sciences, Switzerland
Seán McLoone, Queen's Unviersity Belfast, Ireland
Mahanijah Md. Kamal, Universiti Teknologi MARA, Malaysia
Nadhir Messai, University of Reims Champagne-Ardenne, France
Maciej Michalek, Poznan University of Technology, Poland
Marek Miskowicz, AGH University of Science and Technology, Poland
Paulo Miyagi, University of Sao Paulo, Brazil
Héctor Montes, Technological University of Panama, Panama
Rafael Morales, University of Castilla La Mancha, Spain
Vidal Moreno Rodilla, Universidad De Salamanca, Spain
George Moustris, National Technical University of Athens, Greece

Riccardo Muradore, University of Verona, Italy
Naresh N. Nandola, Siemens Technology, USA
Ciro Natale, Università degli Studi della Campania Luigi Vanvitelli, Italy
Juan J. Nieto, University of Santiago de Compostela, Spain
Shimon Nof, Purdue University, USA
Urbano Nunes, University of Coimbra/Institute of Systems and Robotics, Portugal
Andrzej Obuchowicz, University of Zielona Góra, Poland
Fernando Osorio, USP—Universidade de Sao Paulo, Brazil
Stamatios Papadakis, Department of Preschool Education, University of Crete, Greece
Evangelos Papadopoulos, NTUA, Greece
Ju H. Park, Yeungnam University, Korea, Republic of
Igor Paromtchik, Robotic Technologies, France
Dariusz Pazderski, Poznan University of Technology, Poland
Qingjin Peng, University of Manitoba, Canada
Tadej Petric, Jožef Stefan Institute, Slovenia
Mark Post, The University of York, UK
Raul Marin Prades, Jaume I University, Spain
Radu-Emil Precup, Politehnica University of Timisoara, Romania
Kanty Rabenorosoa, Femto-ST Institute, France
Navid Razmjooy, Independent Researcher, Iran, Islamic Republic of
Oscar Reinoso, Miguel Hernandez University, Spain
Gerasimos Rigatos, Industrial Systems Institute, Greece
Paolo Rocco, Politecnico di Milano, Italy
Alejandro Rodriguez-Angeles, Cinvestav-IPN, Mexico
Raul-Cristian Roman, Politehnica University of Timisoara, Romania
Juha Röning, University of Oulu, Finland
Christophe Sabourin, Université Paris-Est Créteil, LISSI, France
Antonio Sala, Universitat Politecnica de Valencia, Spain
Addisson Salazar, Universitat Politècnica de València, Spain
Javier Sanchis, Universitat Politècnica de València, Spain
Jurek Sasiadek, Carleton University, Canada
Dieter Schramm, University of Duisburg-Essen, Germany
Karol Seweryn, Space Research Centre (CBK PAN), Poland
Antonio Sgorbissa, University of Genova, Italy
Madhavan Shanmugavel, Mechatronics Engineering, SRM Institute of Science and Technology, India
Jinhua She, Tokyo University of Technology, Japan
Milad Siami, Massachusetts Institute of Technology, USA
Vasile Sima, Technical Sciences Academy of Romania, Romania
Azura Che Soh, Universiti Putra Malaysia, Malaysia
Paolo Stegagno, University of Rhode Island, USA
Adrian-Mihail Stoica, Polytechnic University Bucharest, Romania
Olaf Stursberg, University of Kassel, Germany
József Tar, Óbuda University, Hungary

Tomasz Tarczewski, Nicolaus Copernicus University, Poland
Daniel Thalmann, Ecole Polytechnique Federale de Lausanne, Switzerland
Gui Tian, Newcastle University, UK
Germano Torres, PS Solutions, Brazil
Andrés Úbeda, University of Alicante, Spain
José Valente de Oliveira, Faculdade de Ciências e Tecnologia, DEEI, Universidade do Algarve, Portugal
Luigi Villani, Università di Napoli Federico II, Italy
Blas Vinagre, University of Extremadura, Spain
Antonio Visioli, University of Brescia, Italy
Damir Vrancic, Jožef Stefan Institute, Slovenia
Qiangda Yang, Northeastern University, China
Sho Yokota, Toyo University, Japan
Hongchuan Yu, Bournemouth University, UK
Jie Zhang Newcastle University, UK
Cezary Zielinski, Warsaw University of Technology, Poland

Additional Reviewers

Fabiano Correa, University of Sao Paulo, Brazil
Raul Cruz-Morales, UNAM-FES-Cuautitlan, Mexico
Luís Garrote, ISR-UC, Portugal
Vesna Javor, Independent Researcher, Serbia
Abdelhai Lati, University of Ouargla, Algeria
Balazs Nemeth, Institute for Computer Science and Control, Hungary
Pouya Panahandeh, University of Waterloo, Canada
João Paulo, Instituto de Sistemas e Robótica (ISR-UC), Portugal
Ricardo Pereira, Instituto de Sistemas e Robótica (ISR-UC), Portugal
Nenad Petrovic, University of Nis, Faculty of Electronic Engineering, Serbia
Rafal Sobanski, Poznan University of Technology, Poland
Xinyue Wang, University of Paris-Saclay, France

Invited Speakers

Luís Paulo Reis, University of Porto, Portugal
Wim Michiels, KU Leuven, Belgium
Anuradha Annaswamy, MIT, USA
Sergio M. Savaresi, Politecnico di Milano, Italy

Preface

The present book includes extended and revised versions of a set of selected papers from the 20th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2023), held in Rome, Italy, from 13 to 15 November 2023.

The purpose of ICINCO is to bring together researchers, engineers and practitioners interested in the application of informatics to Control, Automation and Robotics. Four tracks covered Intelligent Control Systems, Optimization, Robotics, Automation, Signal Processing, Sensors, Systems Modelling and Control, and Industrial Informatics. Informatics applications are pervasive in many areas of Control, Automation and Robotics; this conference intends to emphasize this connection.

ICINCO 2023 received 180 paper submissions from 47 countries, of which 10% were included in this book.

The papers were selected by the event chairs and their selection was based on a number of criteria that included the classifications and comments provided by the program committee members, the session chairs' assessment and also the program chairs' global view of all papers included in the technical program. The authors of selected papers were then invited to submit revised and extended versions of their papers having at least 30% innovative material.

This collection of papers provides valuable insights into the latest breakthroughs in Informatics applied to Control, Automation and Robotics. The papers address a wide range of trends and challenges, showcasing advancements in areas like: System Modelling and Optimization, Robot Path Planning and Motion Control, Control Systems, Navigation and sensing, Autonomous Agents, and Engineering Applications to Autonomous Ground and Underwater Vehicles, Process Control, Resource Allocation, and others.

We would like to thank all the authors for their contributions and also the reviewers who have helped ensuring the quality of this publication.

Milan, Italy — Giuseppina Gini
Eindhoven, The Netherlands — Henk Nijmeijer
Dearborn, USA — Dimitar Filev
November 2023

Contents

Robotics and Automation

Signal Processing, Sensors, Systems Modelling and Control

Intelligent Control Systems and Optimization

Sparse Convolutional 3D Neural Networks for the Assessment of Environment Traversability

Antonio Santo, Arturo Gil, David Valiente, Álvaro Martínez, and Enrique Heredia

Abstract Ensuring accurate assessment of the surrounding environment is crucial for the efficient operation of autonomous mobile robots, especially when faced with the complexities of unfamiliar and natural terrain that lacks a predefined structure. In this context, traversability assessment is presented as a fundamental component of the autonomous navigation. This research introduces a systematic methodology that employs a LiDAR sensor to capture detailed 3D point clouds, thus facilitating the analysis of traversability regions on both conventional roads and natural scenarios. The proposed approach integrates a well-structured sparse encoder-decoder configuration with rotation invariant features. This configuration is meticulously designed to replicate the input data by associating the acquired traversability features to each individual point in the 3D point cloud. Experimental results confirm the robustness and effectiveness of our method, especially in outdoor environments. Notably, our approach outperforms existing methodologies, making a significant contribution to the ongoing progress in the field of autonomous robotic navigation.

Keywords Autonomous mobile robots · Artificial intelligence · Neural networks

A. Santo (✉) · A. Gil · D. Valiente · Á. Martínez · E. Heredia
University Institute for Engineering Research, Miguel Hernández University, Elche, Alicante, Spain
e-mail: a.santo@umh.es

A. Gil
e-mail: arturo.gil@umh.es

D. Valiente
e-mail: dvaliente@umh.es

Á. Martínez
e-mail: alvaro.martinezb@umh.es

E. Heredia
e-mail: e.heredia@umh.es

A. Santo
Valencian Graduate School and Research Network of Artificial Intelligence (valgrAI), Valencia, Spain

G. Gini et al. (eds.), *Informatics in Control, Automation and Robotics*, Lecture Notes in Electrical Engineering 1436, https://doi.org/10.1007/978-3-031-94989-0_9

1 Introduction

The answer to the question "Where should I walk?", as stated in [36], implicitly includes a global understanding of the robot's environment. This concept, which is considered a natural ability for humans, should be extended to autonomous mobile robots. The application of this innate understanding will greatly enhance the capabilities of autonomous mobile robots and enable them to operate successfully in a wide range of applications, such as exploration of unfamiliar environments, autonomous driving, and search and rescue missions.

While traversability estimation has been recognised as a crucial capability for mobile robots, their historical focus has been simply on the task of obstacle avoidance. In this context, the robot's primary goal is to avoid any physical contact with its environment and to navigate exclusively in open spaces, taking measurements from proximity sensors. This emphasis on traversability estimation made it a sine qua non of a successful path planner.

To date, path planning algorithms have been classified according to two main principles: (a) the definition and representation of spatial information; (b) the delimitation of traversable regions on the map. Regarding the former, various spatial representations have emerged, such as 2D occupancy maps [20], elevation maps (DEMs) [18] and voxel-based 3D occupancy maps [11, 13, 21]. In these representations, the determination of whether a particular space is free or occupied is made by a probabilistic value, which affords the efficient navigation of these spaces by a robotic entity, taking into account the inherent physical parameters of the robotic system.

Nevertheless, the classical approaches mentioned earlier exhibit limited robustness when applied across diverse environmental contexts [39], since the definition of self-driving relies on the specific properties of each environment. In structured environments, the geometries constituting traversable spaces are typically characterized by homogeneity and uniformity. In contrast, in natural environments, this concept becomes inherently more tricky due to the absence of human supervision.

The combination of various factors, along with the advancement of sensors in terms of cost, resolution, and weight, is leading to reconsideration of how we assess traversability. With the rise of supervised learning in recent years, there's a growing shift towards applying this new approach to estimate traversability. Specifically, using neural networks alongside LiDAR sensors has gained popularity because LiDAR is not affected by different lighting conditions, unlike others optical sensors such as cameras.

This paper introduces a novel contribution to traversability estimation in complex terrains through the application of deep learning techniques, specifically segmentation methods of scenes described by 3D point clouds. The subsequent sections are structured as follows: Section 2 provides a brief overview of significant approaches in the realm of Deep Learning for traversability estimation. Moving forward, Sect. 3 elaborates on the fundamental concepts that form the basis of our proposed method, providing a detailed explanation. The paper then proceeds, in Sect. 4, to present a various experimental results covering different types of environments used during the training process. Finally, in Sect. 5, the main conclusions drawn from this innovative approach are summarized.

2 Related Work

By its own fuzzy definition, the estimation of traversability has been approached from different perspectives over the years; from the study of road characteristics [29], to the philosophical and psychological study of what it means to be able to traverse a space [30]. However, the most common context in which this concept has a strong influence is autonomous driving.

In this context, research on traversability estimation methods involves both algorithms commonly employed in the conventional machine learning (ML) domain and more current procedures such as neural networks.

In conventional ML, algorithms typically operate on alternative data representations, emphasizing features identified as discriminative for the specific problem. Thus, [2] employ stereo image pairs as input data to perform a traversability study in challenging environments by extracting geometric and appearance-based features and then classifying them using an SVM algorithm defined in [32], concluding that features including normal vectors are the most suitable for the task. In [16] the authors propose the distinction of three classes, soil, vegetation or object, by means of the extraction of discriminant features based on points and their neighborhoods, since the information provided by an isolated point is not sufficiently reliable to draw conclusions. The proposal incorporates an adaptive neighborhood radius to address the inherent challenge of point density loss relative to the distance from the sensor, a common property of LiDAR sensors. This adaptive approach ensures that high resolutions are maintained at shorter distances, while simultaneously mitigating the impact of noisy features at longer distances. Furthering this same concept of preventing the effect of data sparsity, in [28], given a sampled 3D point cloud, authors represent the environment as a 2.5D elevation map and employ Bayesian Generalized Kernel Inference defined by [33] to obtain a dense elevation map and subsequently perform the classification of the terrain into traversable and non-traversable. In [19], the authors introduced the Random Forest classifier optimized by a genetic algorithm for the classification of ground types. This approach succeeds in establishing a set of optimal initial parameters by applying the methodology used in genetic algorithms, thus solving the traditional problem of Random Forest classifiers.

In recent years, driven by recent technological advances that facilitate their training and deployment in real-world applications, deep learning techniques appear as a possible candidate to solve this task. The study of three-dimensional spaces, defined by unstructured data such as LiDAR point clouds or images, which often involve nonlinear relationships between variables, is processed by this type of algorithms. Neural networks intrinsically outperform conventional methods in modeling these nonlinear associations and in their ability to learn complex patterns [9, 17].

In particular, LiDAR sensors, which output the spatial coordinates of a set of 3D points representing the first reflection produced by objects illuminated with a collimated laser beam, have promoted the development of efficient approaches for handling three-dimensional data. In [34], for example, point clouds undergo transformation into multichannel images that capture the depth, height, and reflectivity of each point. These images are then processed through dense convolutional layers to discern traversable areas. Another strategy, as proposed [24], involves spherical projections of point clouds, followed by the application of 2D convolutional layers for semantic segmentation.

In contrast, in [35] is introduced a different solution employing octal trees, or *octrees*, to reduce the complexity of the space described by point clouds. This method restricts dense convolution operations to occupied octrees, speeding up computational demands. In [6] is extended this concept by computing space traversability using a convolution operation generalization to n-dimensions and incorporating a sparse encoder-decoder setup [4].

In addition, methods have emerged that combine information from various sensors. In [31] authors take a sequence of RGB images and depth images to predict a local traversability map. The depth information is fed directly into the latent space of the neural network after processing the image sequence and fused with the descriptors in subsequent convolutional blocks, creating a map.

Some other methods have also been developed that combine LiDAR information with image data. The authors of [10] propose a road detection method by merging color information from a camera with range information obtained via LiDAR. This involves projecting point clouds onto corresponding images, which then feed into a 2D convolutional neural network. In [5], authors fuse features extracted from both data types using different neural network architectures. In [3] is suggested a progressive adaptation of LiDAR representation to enhance compatibility with visual information from cameras. This transformation involves converting the point cloud into an alternative representation, emphasizing the distinguishability of roads. So far, all the aforementioned works that fused data from different sensors evaluate traversability in the two-dimensional domain. However, works such as [22], relies on 2D convolutional networks to predict the labels in the image, but carry out the reconversion to the point cloud, performing the relevant reprojection of these labels inferred in the image.

3 Proposed Approach

3.1 Sparse Convolution

Sparse convolution, a fundamental technique in deep learning, has emerged as a valuable approach to optimize computational efficiency in the analysis of sparse data, particularly frequent in three-dimensional environments such as LiDAR point clouds. Unlike traditional dense convolution operations, which consider each input pixel, sparse convolution strategically exploits the sparsity inherent in the data. This is achieved by employing sparse filters or processing only non-zero input values, which substantially reduces the computational burden. By focusing only on relevant features, sparse convolution improves the scalability and efficiency of convolutional neural networks (CNNs) in scenarios where computational resources are a critical consideration.

This is especially advantageous in applications such as robotics or autonomous systems, where the input data often contains sparse spatial information. The increased efficiency of sparse convolution not only speeds up model training and inference, but also makes it suitable for resource-constrained environments, a compelling advance in the field of deep learning methodologies tailored to sparse data representations.

In this way, the application of such a discrete operation on any point cloud, B, must be defined in the following way:

– **Coordinates Tensor**. This is a data element consisting of the coordinates of the points that belong to any point cloud $B = \{(\boldsymbol{p}_i, \boldsymbol{f}_i, l_i),\ i = 1, \ldots, N\}$. This expression incorporates an integer part function for space discretization. The points are modified according to a scaling factor, v, that determines the level of space discretization. Furthermore, it also incorporates the position of the point clouds within the batch, b_i, in order to know what point corresponds to which cloud. As a result, the tensor $\mathbf{T}_\mathrm{C}$ is formally defined as:

$$\mathbf{T}_\mathrm{C} = \begin{bmatrix} b_1 & \bar{p}_1 \\ \vdots & \vdots \\ b_N & \bar{p}_M \end{bmatrix} \tag{1}$$

$$\text{with } \bar{p}_j = floor(\boldsymbol{p}_i) = floor\left(\frac{x_i}{v}, \frac{y_i}{v}, \frac{z_i}{v}\right)$$

Consequently, m points from the point cloud could be discretized within the same voxel $\bar{p}_j$. Taking them into account as a single point with a different features vectors associated. In order to resolve the different features within the same voxel, the expression of the following equation was formulated $\mathbf{T}_\mathrm{F}$.

– **Feature Tensor**. $\mathbf{T}_\mathrm{F}$ stores and averages the features $\boldsymbol{f}i$ corresponding to the m points that occupy the same space, i.e., belong to the same voxel denoted as $\bar{p}_j$. This process involves applying the scale factor v and the integer part function.

$$\mathbf{T}_\mathrm{F} = \begin{bmatrix} \bar{f}_1 \\ \vdots \\ \bar{f}_M \end{bmatrix} \tag{2}$$

$$\text{where } \bar{f}_j = \frac{1}{m}\sum_{i=1}^{m} \boldsymbol{f}_i$$
$$\forall \boldsymbol{f}_i \in \bar{p}_j$$

This kind of pre-processing implies the elimination of spaces where there is no spatial information, i.e. there are no points detected by the LiDAR. The input data is carried out using the Minkowski Engine library [4].[1]

3.2 Problem Statement

The task is to evaluate traversability, treating it as solving a semantic segmentation puzzle. A point cloud B is consisting of points defined by Cartesian coordinates, $\boldsymbol{p}_i = (x_i, y_i, z_i)$, feature vectors, $\boldsymbol{f}_i \in \mathbb{R}^{d_{\text{in}}}$, and each point has a traversability label, l_{i}, indicating whether it is traversable (1) or non-traversable (0). The problem is developed as a semantic segmentation task, where the objective is to employ a deep learning model denoted by the mapping function $f : \mathbb{R}^{3+d_{\text{in}}} \rightarrow [0, 1]$, considering both spatial coordinates and associated features, to infer the probability of traversability of each point. Through training on a labeled dataset $\{(\boldsymbol{p}_i, \boldsymbol{f}_i), l_i\}$, the model is responsible for capturing very precise patterns in the point cloud data, allowing it to accurately predict the traversability status of each point.

3.3 Sparse 3D Neural Networks

The methodology for estimating traversability presented in this paper is based on a neural network with an encoder-decoder architecture, whose implementation fuses a sparse version of the Resnet20 [12] neural network and the U-net architecture [26]. As a result, the network can be split into three different parts:

- **Encoder**. The encoder component in our neural network is designed to extract high-level features and representations from the input data, orchestrating a compression of information into a multidimensional feature space. Structured with multiple convolutional layers and pooling operations, this approach gradually decreases the spatial dimensions while enriching the receptive field. Each convolutional layer serves as a discerning observer, capturing diverse levels of abstraction within the input. The downsampling process, facilitated by pooling operations, extends the network's contextual reach, fostering a heightened understanding of complex patterns. In this work, the input data used as feature vector is defined as: $\boldsymbol{f}_i = (n_z, Z)$ where n_z is the Z coordinate of the normal unit vector $\boldsymbol{N}_i$ and the normalized coordinate $Z \in [0, 1]$. This feature vector includes a natural invariance to rotation to the point cloud along the vertical axis.
- **Decoder**. It is a fundamental component of the neural network, plays a key role in the reconstruction process. Its main task is to translate the abstract feature representations obtained from the encoder into a detailed and meaningful output.

[1] https://github.com/NVIDIA/MinkowskiEngine.

It is composed of upsampling layers that restore spatial dimensions, convolutional layers that refine and combine features, and an output layer modified according to the task. In essence, the decoder is the final step of the neural network and transforms the encoded features into a tangible, task-specific output.
- **Residual Block**. As the name suggests, these are convolutional layers that attempt to learn the residual between the input data and its output, understanding the residual as the error or difference between the output and the input. It has been observed that it is easier to learn the residual than just the input. As an added benefit, the network can now learn the identity function simply by setting the residual to zero.

The flow of the point cloud through the neural network shown in Fig. 1 is depicted in a top-down manner on the left-hand side of the image. The point cloud is processed by convolutional layers followed by residual blocks as shown in Fig. 2. Once the encoder finishes, the scheme corresponding to the right part of the image continues in an ascending way, performing the transposed convolutions to recover the initial dimensionality of the starting data and the layers and residual blocks that try to refine the features. In addition, the famous skip connections which are made within the residual block, are extrapolated along the architecture to recover fine details and improve the accuracy of the reconstruction.

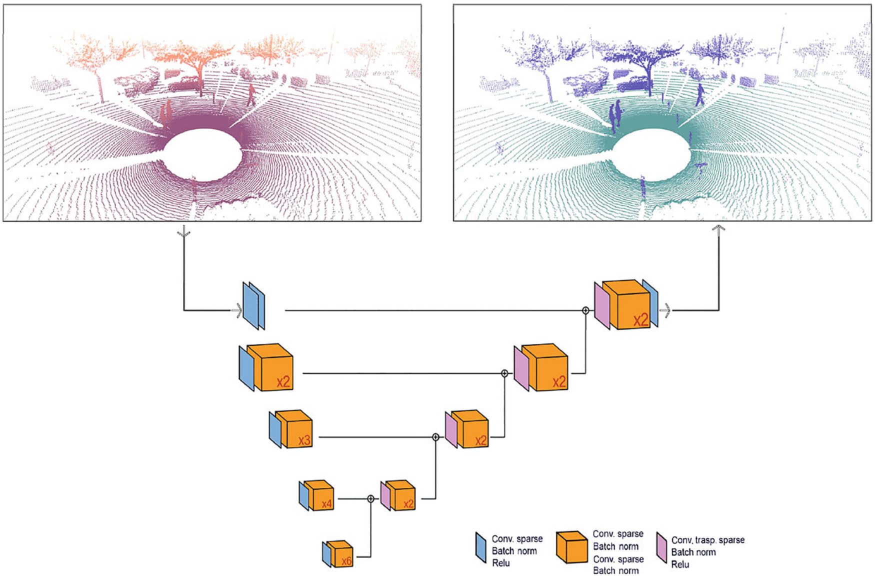


Fig. 1 Encoder-decoder configuration employed, MinkUnet [4, 27]

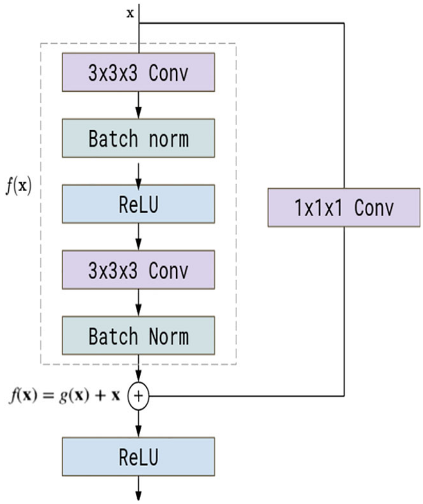


Fig. 2 Residual convolutional block from ResNet

4 Experimental Results

All the experiments of this method have been tested on an Intel Core™ i9-10900X, 20 × 3.70GHz, 128GB RAM platform with NVIDIA RTX 3090 with 24GB VRAM graphic card. The neural network model is implemented using the Minkowski Engine [4], Pytorch and it can be easily integrated into ROS NOETIC. To evaluate the performance of the proposed approach, the following datasets have been employed.

1. *SemanticKITTI* [1]: This dataset is based on the KITTI Vision Benchmark [8], integrating odometry positions and point clouds from various routes through the city of Karlsruhe, Germany, captured by the Velodyne HDL-64E sensor model. It presents a diverse set of scenarios, comprising 22 urban sequences navigating through highly structured environments. These scenarios feature dynamic elements such as moving vehicles and pedestrians, as well as natural elements such as grassy areas, parks and trees. Ten of the 22 sequences are labeled for each point, addressing semantic segmentation challenges within the dataset.
2. *Rellis-3D* [14]: It is a multimodal dataset collected in an off-road environment containing annotations for 13,556 LiDAR scans and 6,235 images. The data was collected on the Rellis Campus of Texas A&M University and presents challenges to existing algorithms related to class imbalance and environmental topography. Experimental results indicate that RELLIS-3D poses challenges to algorithms specifically designed for semantic segmentation in urban environments.
3. *SemanticUSL* [15]: It is a dataset for domain adaptation for LiDAR point cloud semantic segmentation. It contains 1200 point clouds labeled under the same format as the SemanticKITTI including road scenes, pedestrian streets and natural environments.

Table 1 Databases class mapping

Original class	Binary label	Label
Void/Outlier	Eliminated	N/A
Asphalt	Traversable	1
Barrier	Non-traversable	0
Building	Non-traversable	0
Bush	Non-traversable	0
Concrete	Traversable	1
Dirt	Traversable	1
Fence	Non-traversable	0
Grass	Traversable	1
Log	Non-traversable	0
Mud	Traversable	1
Parking	Non-traversable	0
Person	Non-traversable	0
Pole	Non-traversable	0
Puddle	Traversable	1
Road	Non-traversable	0
Rubble	Non-traversable	0
Sidewalk	Traversable	1
Sky	Eliminated	N/A
Traffic Sign	Non-traversable	0
Tree	Non-traversable	0
Vehicles	Non-traversable	0
Water	Traversable	1
Other Object	Non-traversable	0

All of the above databases contain approximately 24 different labels to which a point can belong. These labels are shown in Table 1, with their corresponding conversion, which has been established to be correct under human supervision for the particular traversability problem. Thus, Figures 3, 4, 5 show how the original databases are modified.

4.1 Implementation Details

The training of the model has been improved from the previous version presented in [27]. The differences in optimization strategies, shown in Table 2, contribute to distinct training behaviors and outcomes between the two setups. In the following sections, the results of both configurations will be compared.

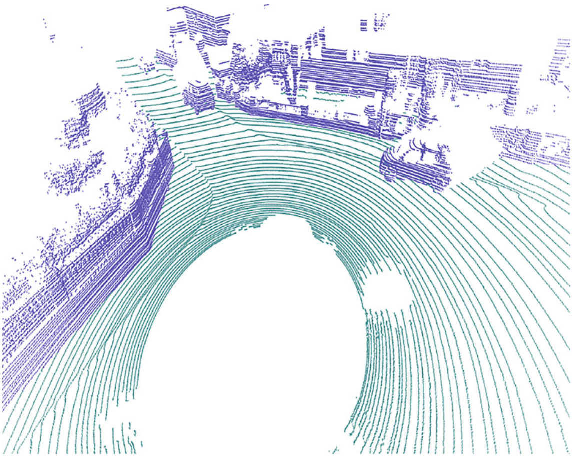


Fig. 3 Point cloud from SemanticKITTI [27]

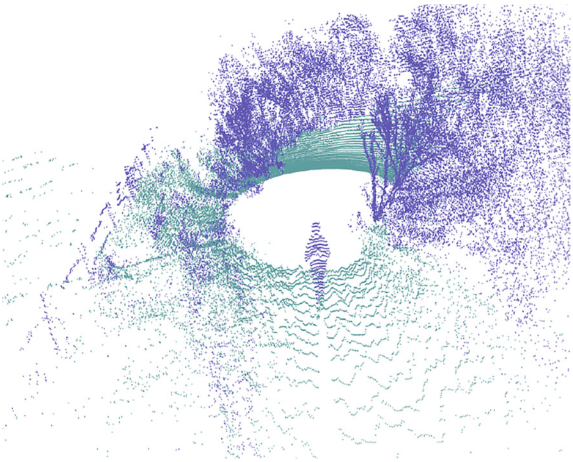


Fig. 4 Point cloud from Rellis-3D [27]

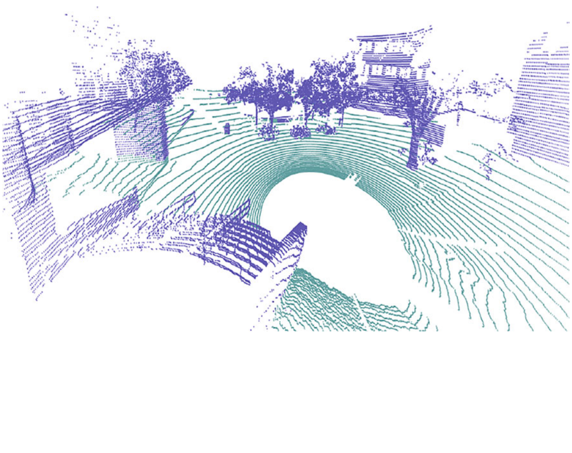


Fig. 5 Point cloud from Semantic-USL [27]

Table 2 Training parameters

Parameters	Basic configuration	Refined
Framework	Minkowski engine	Minkowski engine
Optimizer	SGD	AdamW
Scheduler	None	Cosine
Learning rate	1e-2	1e-2
Weight decay	None	5e-2
Batch size	5	8
Criteria	BCELoss	BCELoss
Epochs	14	9
Rellis-3D	Sequence 1, 2, 3	Sequence 1, 2, 3
Sem. KITTI	Sequence 0, 1, 2, 3	Sequence 0, 1, 2, 3

On the other hand, the training stage of the aforementioned datasets has been carried out with the aim of achieving a multimodal model that performs well in all types of environments without making distinctions between urban and natural environments. Therefore, a balanced number of training examples has been provided to include, equally, both environments and balanced classes. The use of the SemanticUSL database is limited exclusively to testing processes to demonstrate the generalization capability of the network in environments never seen during training.

4.2 *Distance Effect*

It can be observed when analysing the interaction of the LiDAR planes with the surrounding environment that the distance, d, between consecutive LiDAR planes and the ground plane is dependent on the angle formed by the intersection of the two mentioned planes, α, and the height, h, at which the LiDAR is placed. Thus, at very far distances, the different laser planes are far apart. This effect is easy to appreciate in Fig. 6.

Consequently, the representation of some regions of the robot's environment is highly uncertain, since as mentioned above the very sparse nature of LiDAR technology results in a very low density over long distances. Therefore, as a solution, it was proposed to consider only the points that are within a radius of 45 meters from the sensor and, all the evaluations have been performed under this condition. Figures 7 and 8 are in line with the idea described above, and show how metrics such as accuracy and recall of a model trained with raw point clouds do not contribute anything once the distance exceeds 45/50 m, and the metric becomes noisy and inaccurate.

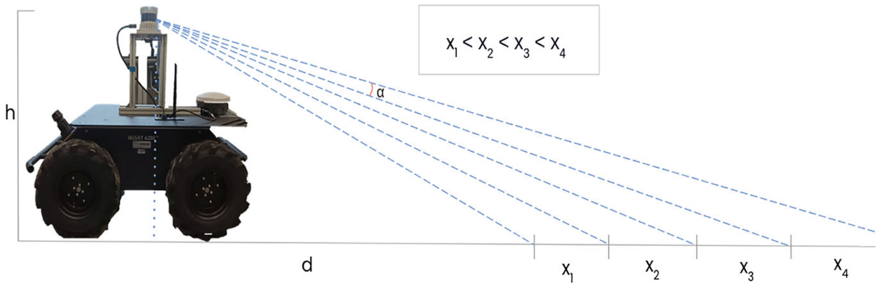


Fig. 6 LiDAR planes interactions with the ground plane

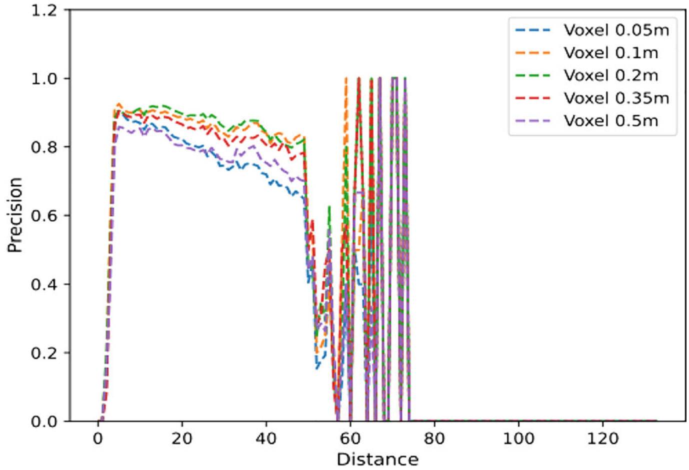


Fig. 7 Precision metric in relation to distance

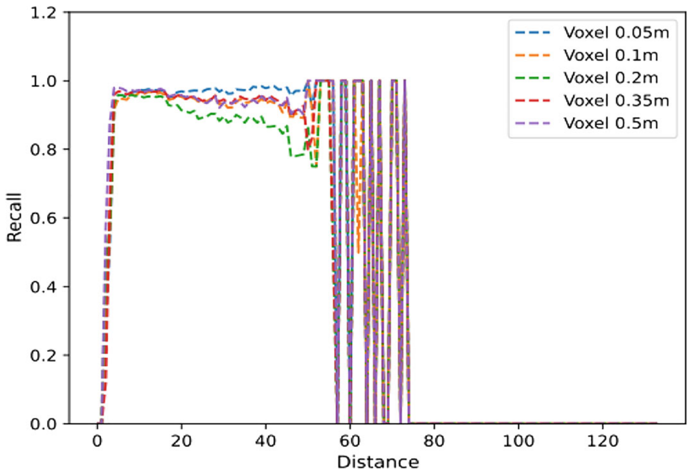


Fig. 8 Recall metric in relation to distance

4.3 Quantitative Evaluation

In regard to the performance of a classification model, the following figures represent the precision and recall curves obtained with the test set data. Specifically, Figures 9 and 11 present the results in urban and structured environments for the SemanticKITTI and USL datasets. In both figures, the precision-recall curve is very close to the maximum (upper right corner). Working levels are achieved at which it does not seem necessary to select a lower recall level to increase precision. Hence, it can be assumed that the trained models consistently learn the traversable and non-traversable zones, achieving accuracy and recall values exceeding 95% for specific operating points. Furthermore, it is proved that how highly structured spaces with a uniform point distribution, as we might have deduced, do not have much relevance for the discretisation of the space (size of voxel, v, or scale parameter).

On the other hand, Fig. 10 presents the results when the method is applied to an unstructured environment. In this context, the results are not as satisfactory. We can see that there are significant differences in performance between the different levels of discretisation, although the explanation for this does not seem to go beyond randomness and the distribution of the points. We can conclude that in this type of environment it is more complex to infer what can be traversed with certainty.

In terms of numerical metrics, Table 3 shows in detail the performance metrics obtained as a function of the scaling factor mentioned above. The result are obtained from the model presented in Fig. 1, with different training processes. One of them corresponds to the method presented in [27] and the left part of the table is about the refined training described in Sect. 4.1. It can be seen how fine-tuned training improves the results in most cases where a small space discretisation is applied, although the metrics are quite similar.

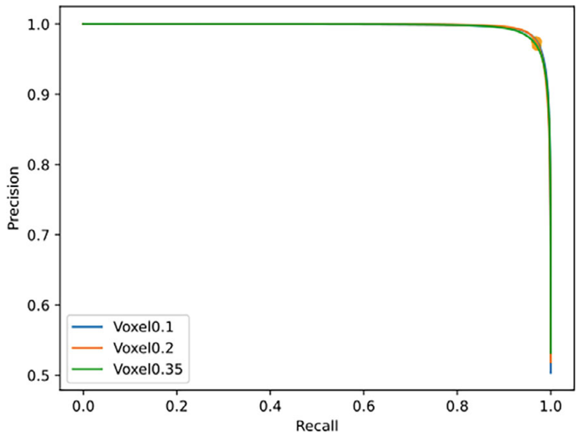
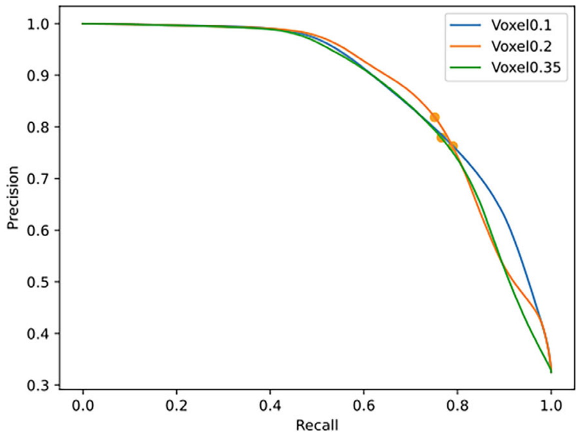


Fig. 9 Precision-recall curve on the SemanticKITTI dataset

In addition, a comparison with methods used in the field of semantic segmentation is presented in Table 4. The comparison has been done by evaluating these methods on SemanticKitti labelled data sequences.

To conclude the experiments, a study of the descriptors extracted by the network has been carried out in relation to the rotation of the input data in the Euler yaw, ψ, angle. Figure 12a, b indicate the changes in terms of precision and recall metrics when rotating a point cloud from 0 to 360 degrees. An ideal graph should show a completely horizontal line. However, due to the discrete nature of space during rotation, the results show slight, albeit minimal, variations. The metrics can be considered to be largely invariant to rotation.

Fig. 10 Precision-recall curve on the Rellis-3D dataset



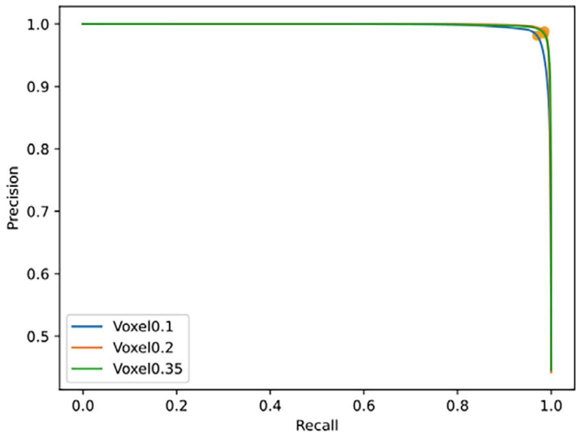
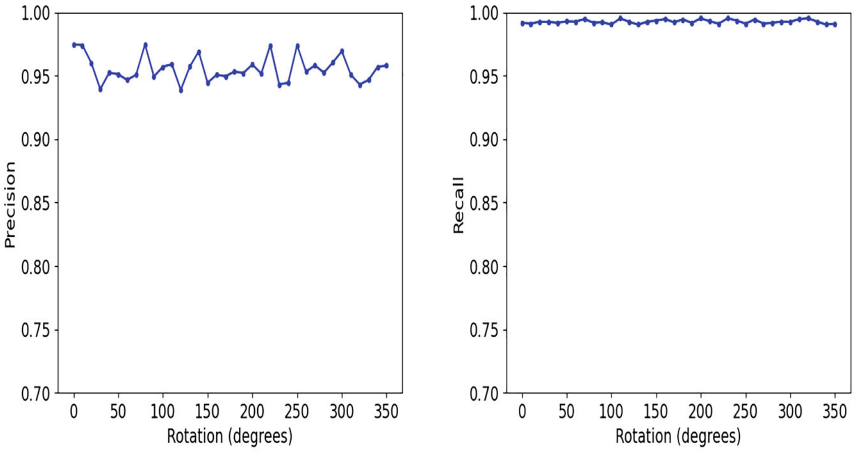


Fig. 11 Precision-recall curve on the USLSemantic dataset

Table 3 Results obtained in inference

		Basic			Fine-tuned		
Dataset	Voxel	F1	Acc	MIOU	F1	Acc	MIOU
Rellis-3D	0.1	0.72	0.83	0.57	0.74	0.82	0.60
Kitti		0.97	0.97	0.95	0.96	0.96	0.93
USL		0.93	0.93	0.87	0.92	0.94	0.85
Rellis-3D	0.2	0.79	0.85	0.66	**0.79**	**0.86**	**0.66**
Kitti		0.97	0.97	0.94	**0.97**	**0.98**	**0.95**
USL		0.93	0.93	0.87	**0.94**	**0.95**	**0.90**
Rellis-3D	0.35	0.79	0.86	0.66	0.75	0.84	0.60
Kitti		0.97	0.97	0.94	0.96	0,97	0.93
USL		0.95	0.95	0.91	0.94	0.94	0.88



(a) Precision metric in relation to rotation. (b) Recall metric in relation to rotation.

Fig. 12 Rotation invariant results

Table 4 Results of different approaches on SemanticKITTI sequences 0–10. With [1]: [25], [2]: [37], [3]: [38], [4]: [23], [5]: [7]

Method	Accuracy	F1	mIoU
[1]	93.4	93.0	87.4
[2]	90.1	89.4	81.4
[3]	92.3	91.9	85.5
[4]	90.0	93.0	87.4
[5]	89.2	91.4	84.9
Previous work	**96.6**	**95.9**	**92.3**
Ours	**96.8**	**96.1**	**92.7**

4.4 Qualitative Evaluation

In Fig. 13, the outcomes are visually depicted, presenting the components of the confusion matrix in distinct colors: true positives (green), true negatives (purple), false positives (red), and false negatives (orange). Figure 13a, c, e showcase accurately labeled point clouds from different evaluated datasets. In contrast, Fig. 13b, d, f illustrate the neural network inferences, highlighting errors in orange and red, and successful predictions in green and purple, following the previously described color scheme. False positives often manifest in highly unstructured regions, while false negatives tend to appear near edges between adjacent geometries.

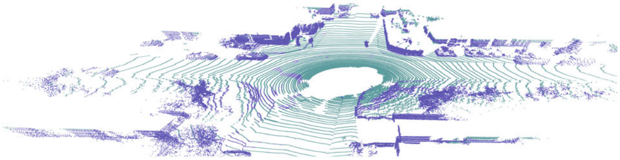
It is crucial to emphasize that false positives, where the network misclassifies non-traversable areas as traversable, pose significant risks in robotic navigation tasks. Additionally, the method's rotation invariance is evident in Fig. 14, displaying neural network inferences for the same point cloud rotated at 45 and 90 degrees in Fig. 14b and c, respectively.

5 Conclusion

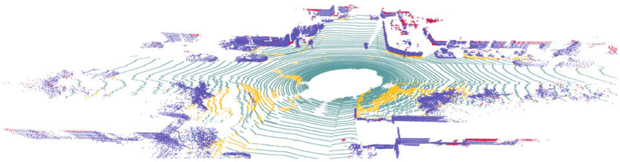
In this paper have been presented a novel approach for traversability estimation in point clouds using a sparse neural network with an encoder-decoder configuration. The main aspects of the paper include the analysis of the impact of voxel size, the study of rotation invariance within the same environment and the presentation of results highlighting the strengths and limitations of the method in various environmental scenarios. The results obtained with the presented approach demonstrate an outstanding performance in the assessment of the traversability in semi-structured environments (SemanticKITTI, SemanticUSL). Nevertheless, the outcomes achieved in highly unstructured scenarios demonstrated lower results.

The extension of the presented approach may benefit for the inclusion of visual information in combination with LiDAR data in order to improve the robustness and consistency, overall in unstructured environments. It is intended to evaluate the performance of the neural network on a variety of robots equipped with various sensors. Furthermore, the future challenge of addressing spatial traversability under a continuous paradigm, where evaluations go beyond binary results and take into account the physical attributes of the robot interacting with the terrain, is identified. In all, the paper lays the foundation for a promising approach to traversability estimation in point clouds and provides a clear roadmap for future improvements and extensions.

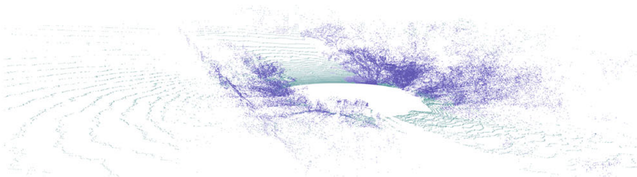
Acknowledgements This work has been funded by the ValgrAI Foundation, Valencian Graduate School and Research Network of Artificial Intelligence through a predoctoral grant.



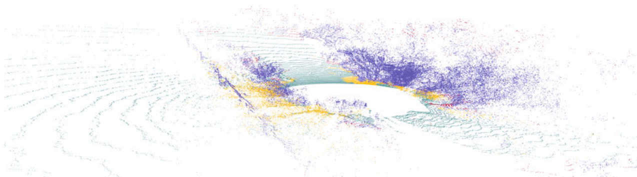
(a) SemanticKITTI inference.



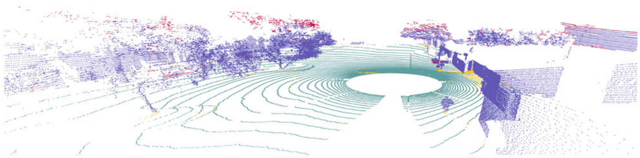
(b) Comparison of inference and ground truth cloud.



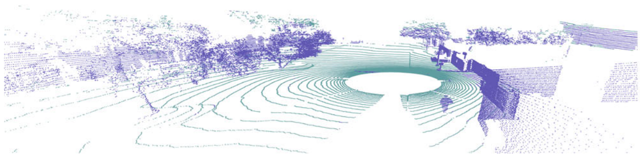
(c) Rellis-3D inference.



(d) Comparison of inference and ground truth cloud.

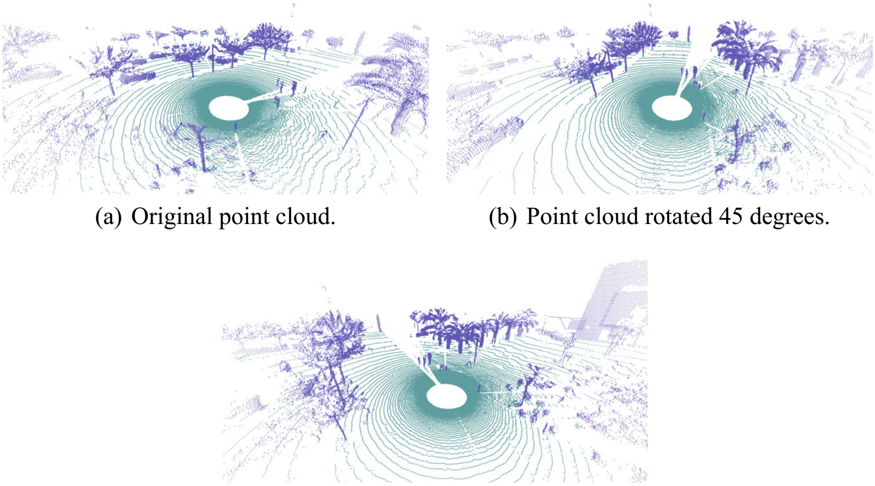


(e) Comparison of inference and ground truth cloud.



(f) USL inference.

Fig. 13 Visual representation of the inference results of the network. Green: true positives (TP). Purple: true negatives (TN). Red: false positives (FP). Orange: false negatives (FN)



(a) Original point cloud. (b) Point cloud rotated 45 degrees.

(c) Point cloud rotated 90 degrees.

Fig. 14 Inference invariant to rotation

References

1. Behley, J., Garbade, M., Milioto, A., Quenzel, J., Behnke, S., Gall, J., Stachniss, C.: Towards 3D LiDAR-based semantic scene understanding of 3D point cloud sequences: the SemanticKITTI dataset. Int. J. Robot. Res. **40**(8–9), 959–967 (2021)
2. Bellone, M., Reina, G., Caltagirone, L., Wahde, M.: Learning traversability from point clouds in challenging scenarios. IEEE Trans. Intell. Transp. Syst. **19**(1), 296–305 (2017)
3. Chen, Z., Zhang, J., Tao, D.: Progressive lidar adaptation for road detection. IEEE/CAA J. Autom. Sinica **6**(3), 693–702 (2019)
4. Choy, C., Gwak, J., Savarese, S.: 4D spatio-temporal convnets: Minkowski convolutional neural networks. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 3075–3084 (2019)
5. Fan, R., Wang, H., Cai, P., Liu, M.: Sne-roadseg: incorporating surface normal information into semantic segmentation for accurate freespace detection. In: European Conference on Computer Vision, pp. 340–356. Springer (2020)
6. Frey, J., Hoeller, D., Khattak, S., Hutter, M.: Locomotion policy guided traversability learning using volumetric representations of complex environments. In: IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 5722–5729. IEEE (2022)
7. Fusaro, D., Olivastri, E., Evangelista, D., Imperoli, M., Menegatti, E., Pretto, A.: Pushing the limits of learning-based traversability analysis for autonomous driving on CPU. In: Intelligent Autonomous Systems 17: Proceedings of the 17th International Conference IAS-17, pp. 529–545. Springer (2023)
8. Geiger, A., Lenz, P., Urtasun, R.: Are we ready for autonomous driving? the Kitti vision benchmark suite. In: IEEE Conference on Computer Vision and Pattern Recognition, pp. 3354–3361. IEEE (2012)
9. Georgiou, T., Liu, Y., Chen, W., Lew, M.: A survey of traditional and deep learning-based feature descriptors for high dimensional data in computer vision. Int. J. Multimed. Inf. Retr. **9**(3), 135–170 (2020)

10. Gu, S., Zhang, Y., Tang, J., Yang, J., Kong, H.: Road detection through CRF based lidar-camera fusion. In: International Conference on Robotics and Automation (ICRA), pp. 3832–3838. IEEE (2019)
11. Han, L., Gao, F., Zhou, B., Shen, S.: Fiesta: fast incremental Euclidean distance fields for online motion planning of aerial robots. In: IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 4423–4430. IEEE (2019)
12. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 770–778 (2016)
13. Hornung, A., Wurm, K.M., Bennewitz, M., Stachniss, C., Burgard, W.: Octomap: an efficient probabilistic 3D mapping framework based on octrees. Auton. Robot. **34**, 189–206 (2013)
14. Jiang, P., Osteen, P., Wigness, M., Saripalli, S.: Rellis-3D dataset: data, benchmarks and analysis. In: IEEE International Conference on Robotics and Automation (ICRA), pp. 1110–1116. IEEE (2021)
15. Jiang, P., Saripalli, S.: Lidarnet: a boundary-aware domain adaptation model for point cloud semantic segmentation. In: IEEE International Conference on Robotics and Automation (ICRA), pp. 2457–2464. IEEE (2021)
16. Kragh, M., Jørgensen, R.N., Pedersen, H.: Object detection and terrain classification in agricultural fields using 3D lidar data. In: Proceedings of the 10th International Conference on Computer Vision Systems (ICVS 2015), pp. 188–197, Copenhagen, Denmark, 6–9 July 2015. Springer (2015)
17. Lai, Y.: A comparison of traditional machine learning and deep learning in image recognition. J. Phys. Conf. Ser. **1314**, 012148 (2019). IOP Publishing
18. Langer, D., Rosenblatt, J., Hebert, M.: A behavior-based system for off-road navigation. IEEE Trans. Robot. Autom. **10**(6), 776–783 (1994)
19. Liao, W.: Ground classification based on optimal random forest model. In: IEEE International Conference on Control, Electronics and Computer Technology (ICCECT), pp. 709–714. IEEE (2023)
20. Moravec, H., Elfes, A.: High resolution maps from wide angle sonar. In: Proceedings of the IEEE International Conference on Robotics and Automation, vol. 2, pp. 116–121. IEEE (1985)
21. Oleynikova, H., Taylor, Z., Fehr, M., Siegwart, R., Nieto, J.: Voxblox: incremental 3D Euclidean signed distance fields for on-board Mav planning. In: IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 1366–1373. IEEE (2017)
22. Paz, D., Zhang, H., Li, Q., Xiang, H., Christensen, H.I.: Probabilistic semantic mapping for urban autonomous driving applications. In: IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 2059–2064. IEEE (2020)
23. Qi, C.R., Su, H., Mo, K., Guibas, L.J.: Pointnet: deep learning on point sets for 3D classification and segmentation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 652–660 (2017)
24. Razani, R., Cheng, R., Taghavi, E., Bingbing, L.: Lite-hdseg: Lidar semantic segmentation using lite harmonic dense convolutions. In: IEEE International Conference on Robotics and Automation (ICRA), pp. 9550–9556. IEEE (2021)
25. Redmon, J., Farhadi, A.: Yolov3: an incremental improvement (2018). Preprint at arXiv:1804.02767
26. Ronneberger, O., Fischer, P., Brox, T.: U-net: Convolutional networks for biomedical image segmentation. In: Proceedings of the 18th International Conference on Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015, vol. 18, Munich, Germany, 5–9 Oct 2015, Part III, pp. 234–241. Springer (2015)
27. Santo., A., Gil., A., Valiente., D., Ballesta., M., Peidró., A.: Computing the traversability of the environment by means of sparse convolutional 3d neural networks. In: Proceedings of the 20th International Conference on Informatics in Control, Automation and Robotics (ICINCO), vol. 1, pp. 383–393. INSTICC, SciTePress (2023). https://doi.org/10.5220/0012160300003543
28. Shan, T., Wang, J., Englot, B., Doherty, K.: Bayesian generalized kernel inference for terrain traversability mapping. In: Conference on Robot Learning, pp. 829–838. PMLR (2018)

29. Tsukada, Y., Okutani, T., Itsubo, S., Tanabe, J.: Evaluation of roads network in japan from viewpoint of drivability. In: Proceedings of the Eastern Asia Society for Transportation Studies, vol. 6 (The 7th International Conference of Eastern Asia Society for Transportation Studies, 2007), pp. 336–336. Eastern Asia Society for Transportation Studies (2007)
30. Uğur, E., Şahin, E.: Traversability: a case study for learning and perceiving affordances in robots. Adapt. Behav. **18**(3–4), 258–284 (2010)
31. Valverde Gasparino, M., Narenthiran Sivakumar, A., Chowdhary, G.: Wayfaster: a self-supervised traversability prediction for increased navigation awareness. arXiv e-prints: 2402 (2024)
32. Vapnik, V.: The Nature of Statistical Learning Theory. Springer Science & Business Media (1999)
33. Vega-Brown, W.R., Doniec, M., Roy, N.G.: Nonparametric Bayesian inference on multivariate exponential families. Adv. Neural Inf. Process. Syst. **27** (2014)
34. Velas, M., Spanel, M., Hradis, M., Herout, A.: CNN for very fast ground segmentation in Velodyne lidar data. In: IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC), pp. 97–103. IEEE (2018)
35. Wang, P.S., Liu, Y., Guo, Y.X., Sun, C.Y., Tong, X.: O-CNN: octree-based convolutional neural networks for 3D shape analysis. ACM Trans. Graph. (TOG) **36**(4), 1–11 (2017)
36. Wellhausen, L., Dosovitskiy, A., Ranftl, R., Walas, K., Cadena, C., Hutter, M.: Where should i walk? predicting terrain properties from images via self-supervised learning. IEEE Robot. Autom. Lett. **4**(2), 1509–1516 (2019)
37. Wu, B., Wan, A., Yue, X., Keutzer, K.: Squeezeseg: convolutional neural nets with recurrent CRF for real-time road-object segmentation from 3D lidar point cloud. In: IEEE International Conference on Robotics and Automation (ICRA), pp. 1887–1893. IEEE (2018)
38. Wu, B., Zhou, X., Zhao, S., Yue, X., Keutzer, K.: Squeezesegv2: improved model structure and unsupervised domain adaptation for road-object segmentation from a lidar point cloud. In: International Conference on Robotics and Automation (ICRA), pp. 4376–4382. IEEE (2019)
39. Xiao, X., Liu, B., Warnell, G., Stone, P.: Motion planning and control for mobile robot navigation using machine learning: a survey. Auton. Robot. **46**(5), 569–597 (2022)