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TOWARDS AUTOMATED APRON OPERATIONS - TRAINING OF NEURAL NETWORKS FOR SEMANTIC SEGMENTATION USING SYNTHETIC LIDAR SENSORS

Michael Schultz

Institute of Flight Systems
Bundeswehr University Munich
85577 Neubiberg
GERMANY

Stefan Reitmann
Bernhard Jung

Institute of Informatics
Freiberg University of Mining and Technology
Akademiestrasse 6, 09599 Freiberg
GERMANY

Sameer Alam

Saab-NTU Joint LabSingapore
Nanyang Technological University
Nanyang Ave, 639798 Singapore
SINGAPORE

ABSTRACT

For safe operations at the airport apron, controllers are supported by an appropriate sensor environment. Deep learning models could improve the classification of observed objects, but these models require a large amount of data to be trained. Therefore, we developed a virtual airport environment to generate the required training and validation data for any operational scenario. A synthetic LiDAR sensor is implemented in this environment and applied at Singapore Changi Airport. Using different data sources, the airport infrastructure and objects are modeled and a multitude of 3D scenes are generated. From these scenes, a point cloud is extracted from the LiDAR sensor feedback. This point cloud is already labeled by the underlying models (ground truth) and serves as input for PointNet++ to be trained for efficient segmentation and classification. We show that the training with synthetic input data is a promising approach even assuming degradation of the sensor feedback.

1 INTRODUCTION

The improvement of operational performance is a key driver of the implementation of artificial intelligence (AI) solutions in air traffic management (ATM). In this context, digital twins of airports are developed to extend testing and validation capabilities for operations, which demands procedures and tools to check algorithms and especially train implemented AI solutions on-premise or in the cloud. Apron operations have to ensure both high utilization of given capacity and safe aircraft operations even under degraded environmental conditions, such as low visibility. Not only could our approach be used to provide additional information about apron operations to enhance situational awareness, but it can also be used to improve safety by automatically detecting unexpected or unknown objects.

This paper deals with the analysis of light detection and ranging (LiDAR) technology within the airport environment, whose evaluation by deep learning can provide great added value to identify elements on the apron. LiDAR is a distance measurement technique that involves pointing a laser at an object. The distance is then determined by the time it takes for the reflected light to return to the receiver.

The basic problem of deep learning models is the amount of data needed to train and learn the knowledge. This would require a large number of real measurements covering a wide range of scenarios. Especially for special operational cases, which have to be analyzed with LiDAR, this is hardly possible. For this reason, we propose a prototype for a synthetic data generator in the airport environment using Singapore Changi Airport (WSSS) as a reference. With the help of different data sources and our own models, a multitude of 3D scenes can be generated which correspond to the real operational environment. Point clouds are extracted from these scenes according to the specifications of a LiDAR sensor (cf. Reitmann et al. (2021)). In this context, a point cloud is a set of data points in space that represent a 3D shape or object. These point clouds are already labeled by the underlying model and serve as input to PointNet++ (Qi et al. 2017; Qi et al. 2017) for further segmentation and classification.

We show that the training of a classifier based on artificial input data is a promising approach, which covers relevant aspects of the real system and can therefore be easily applied at any airport. In particular, we expect to significantly support apron controllers in (remote) tower environment (integrated tower working position (Eurocontrol 2020a)). With the implementation of remote towers (external visual and also location-independent aerodrome control), the working environment of apron controllers was also extended by the use of technologies to augment the standard 'out of the window' view. Information from different sensors (e.g., surface movement radar) and sensor networks (Eurocontrol 2020b) could be represented on the monitors used at the upgraded workstations. Furthermore, current developments clearly aim at a more automated environment, which will step-wise shift the current controller tasks to supervision. In the future apron control, LiDAR sensors will provide additional features for safe and reliable operations. They combine certain characteristics that stand out from the established sensors, such as non-cooperative detection, large detection angles, high pulse emission frequencies, pulse emission at extremely high frequencies, and high precision and accuracy in the millimeter range. We assume that the continuous enhancement of both sensor hardware and algorithms, implementation of remote towers, and upgrade of current controller workstations will result in more efficient handling of complex traffic situations.

1.1 Literature Overview

With our contribution, we are entering a new field of application of data analytics and machine learning in aviation. Research in this context is primarily addressing aircraft trajectory management. Here, clustering represents a fundamental concept for recognizing and providing a better insight into patterns in traffic flows (Basora et al. 2017; Basora et al. 2018; Gariel et al. 2011; Olive and Morio 2019). These approaches enable the prediction of trajectories (Lv et al. 2015; Di Ciccio et al. 2016; Liu et al. 2018) and the detection of non-nominal operations (Das et al. 2010; Olive et al. 2018; Olive and Bieber 2018; Basora et al. 2019).

This does not only result in new innovative approaches for future air traffic concepts, such as a dynamic airspace management (Gerdes et al. 2018; Gerdes et al. 2020), but also a data-driven provision of open-data aircraft performance models (Sun et al. 2018; Sun 2019; Rosenow et al. 2022). The latter in particular opens up non-limiting, restriction-free, non-discriminatory, and comparative implementation and evaluation of flight performance and flight management concepts from a variety of flying platforms to all researchers. OpenAP (Sun et al. 2020) has been developed as an open-source aircraft performance model, and BlueSky (Hoekstra and Ellerbroek 2016) is a simulation environment for research into air traffic management and air traffic flow. In addition to addressing airspace and air traffic management challenges, research focuses on determining airport performance by analyzing the impact of local weather events on the flow of arriving and departing aircraft (Reitmann and Schultz 2018; Schultz et al. 2021). In this context, runway and apron operations also have significant implications for the airport's capacity (Olive and Bieber 2018; Herrema et al. 2019; Schultz et al. 2019; Schultz et al. 2022) as do aircraft ground and turnaround processes (Schultz and Reitmann 2019).

Recognizing the position, orientation, and direction of movement of aircraft is critical for ground movements. The LiDAR concept offers a suitable technology for this purpose, which is already being successfully applied in the automotive sector and could also open up new applications in aviation. One of the main interests in the aviation domain is the detection of known and unknown objects on the airport apron (Koppanyi and Toth 2015; Börcs et al. 2017; Kusenbach et al. 2016). The significant influence of weather on sensor feedback plays as much a role (Radecki et al. 2016; Goodin et al. 2019; Bijelic et al. 2018) as the determination of detection accuracies and development of benchmark scenarios in realistic deployment scenarios (Brassel et al. 2019; Mund et al. 2014). The use of deep learning methods requires a large amount of data, which can currently only be provided by artificially generated sample data. However, this area is still relatively unexplored.

1.2 Focus and Structure of the Document

The main focus of our research is the consideration of possible sensor errors already in a synthetic sensor environment, providing a large amount of training data. We assume that a learned error correction in the virtual test environment will facilitate the transfer to a real working environment. Also, sensor weaknesses detected later in the field can be specifically introduced into the sensor simulation to further increase the accuracy of sensor feedback. We develop a synthetic 3D experimental airport environment of Singapore Changi Airport (WSSS) in which we can implement synthetic sensor technologies and operational processes on the apron, such as moving aircraft or ground handling vehicles. This environment provides a large set of point clouds as sensor feedback focusing on both different operational scenes and the mode of operation of the LiDAR sensor. To anticipate the weather dependency of LiDAR sensors we add an error function, which affects the sensor feedback by data dropouts and erroneous data points. All point clouds are segmented and classified using a deep learning approach.

The paper is structured as follows. After the introduction and the brief literature overview (Section 1), Section 2 addresses the synthetic data generation. We describe the setup of the airport environment (infrastructure and vehicles) and the general approach to implementing synthetic LiDAR sensors using BLAINDER (Reitmann et al. 2021). In Section 3, information about our machine learning approach is provided, the experimental setup is introduced (three scenarios) and the results are presented. Finally, the paper ends with a conclusion and an outlook on future research (Section 4).

2 SYNTHETIC DATA GENERATION

Point clouds are the raw output of many different sensors, such as LiDAR and RGB-D (depth cameras). Thus, those are the main sources from which point clouds are generated. But one can also generate a point cloud from a triangular mesh using *mesh sampling* (Zhou et al. 2018). To transform our synthetic 3D scenes of meshes into a LiDAR-like point cloud, we use LiDAR-like operations of BLAINDER (Reitmann et al. 2021) within a virtual airport environment (3D model of WSSS). Figure 1 exhibits our approach for the synthetic data integration.

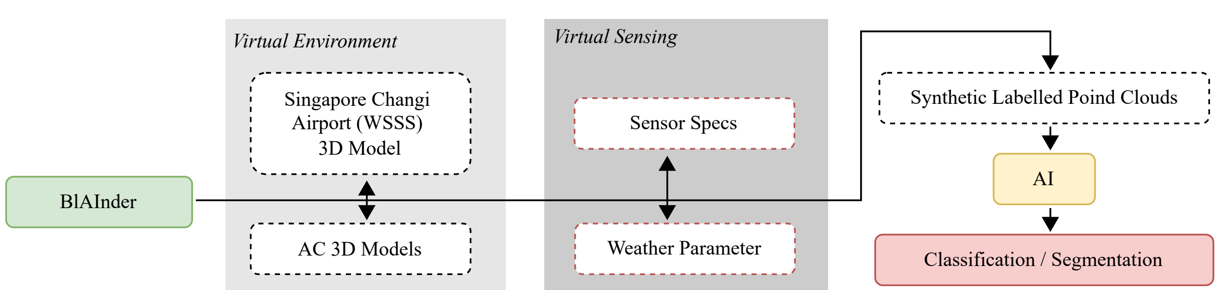


Figure 1: Basic approach for synthetic data integration into an AI pipeline.

A point cloud is an important type of geometric data structure. In the basic setting, each point is represented by three coordinates (x,y,z). Additional dimensions may be added by computing normals and other local or global features (like RGB value, or feature ID). Thus, a point cloud P consists of $n \in \mathbb{Z}_0^+$ tuples of (x,y,z) coordinates, extended by further information. This unordered, but mathematically clear formulated structure makes it possible to apply different methods to find related groups representing objects within a scene.

The point clouds in this work are derived from feedback from synthetic LiDAR sensors. LiDAR is a laser-based method to determine distances between the sensor and any object holding a reflective surface by measuring the travel time of the laser trace. As a consequence, objects or parts of them that cannot be touched from the sensor position (e.g., obscured by other objects) cannot be part of the resulting point cloud. Thus, point clouds of the LiDAR sensor often do not fully represent observed objects in realistic environments. In addition, the circular propagation of the LiDAR laser beam from a certain point reduces the point density with increasing distance of the objects. Therefore it is necessary to find out if and in which quality object recognition based on these point clouds is applicable for different object distances and poses (position and orientation). Classification and segmentation are two main applications for point clouds (Qi et al. 2017). We use both techniques deep learning techniques as a combined approach for understanding point cloud data. While segmentation is a partition of an image into several coherent parts, without any attempt at understanding what these parts represent, classification is used to assign fixed labels to a group of points identified as belonging together. Semantic segmentation achieves fine-grained inference by making dense predictions inferring labels for every pixel so that each pixel is labeled with the class of its enclosing object core region. This approach helps to classify objects within a scene.

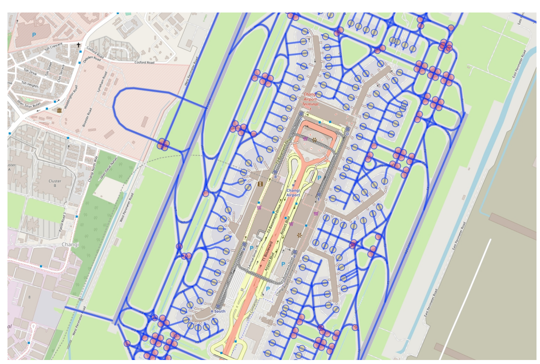
2.1 Scene Setup

We use the open-source software Blender to create and model a custom scene of triangular meshes representing WSSS infrastructure. The model is shown in Figure 2, where Blender is used to model the basic objects of the scene (except aircraft). The scene objects are divided into static and dynamic in terms of the model and pose. The dynamic of poses includes translation and rotation. Scaling was normalized in Blender and brought to a scale with the aircraft. This includes the information on whether an object is changeable in its form (different aircraft types, but constant class/label), static in its format but pose-dynamic (ground vehicles, fingers), or completely static (buildings).

Free data is available to further enhance the airport model. For example, data from OpenStreetMap (e.g., parking positions, runways, taxiways) can already be accessed pre-filtered via defined interfaces.

Simple filter using https://overpass-turbo.eu/.

```
// fetch area \airport" to search in
area[icao~"WSSS"]->.searchArea;
// gather results
(
  nwr(area.searchArea)
  ["aeroway"~"parking_position|taxiway|runway"];
);
out body;
>;
out skel qt;
```



Representing aircraft operations at the airport apron requires a variety of aircraft types in many different poses. For this purpose, we used the research data set ShapeNetCore.v2 (Chang et al. 2015) and included the necessary aircraft models from the category 'aircraft, aeroplane, plane/transport airplane' and further 3D objects related to the operational airport environment, such as ground vehicles, towbars, or passenger bridges as elements of the terminal infrastructure (see Figure 3).

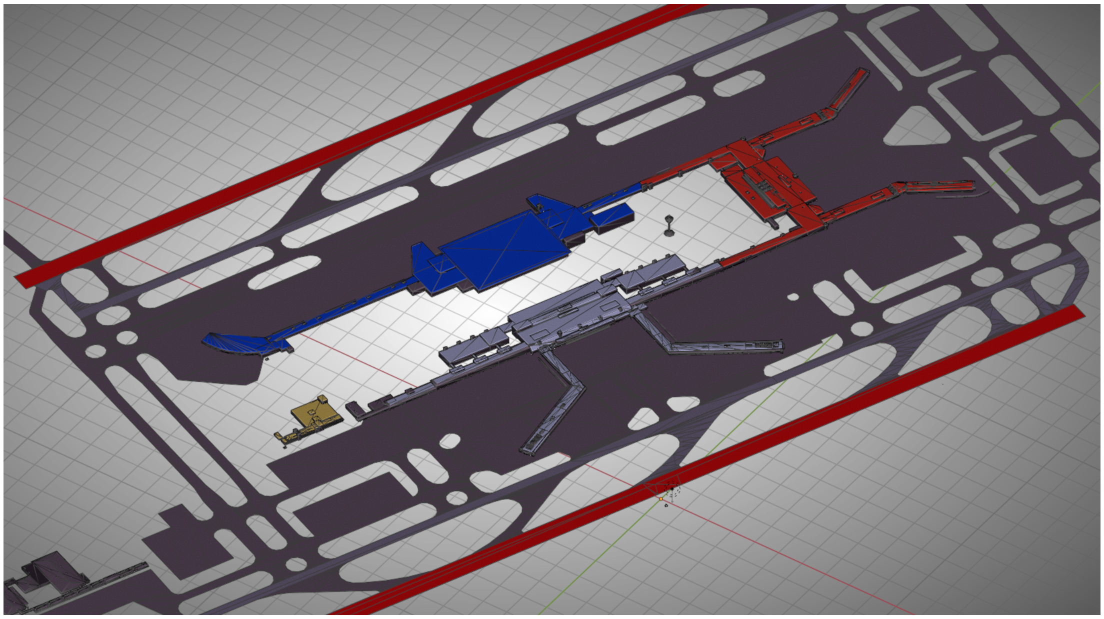


Figure 2: Singapore Changi Airport - 3D Model with a polygon count of 29.412.

In terms of safety cases, for example, the tow bar (see Figure 3(b)) could be considered an unexpected or unknown object in test scenarios. Tow bars are used to push aircraft back from their positions or to tug them from one position to another (e.g., for maintenance). These bars sometimes are occasionally left at inappropriate apron positions and hold the potential to be overlooked by operators. Due to their size and weight, they are difficult to detect by surveillance systems but are potential sources of danger. Although the virtual environment allows the object database to be constantly expanded, on the other hand, all objects must first be modeled and positioned in a scene in order to be able to detect them with synthetic sensors.

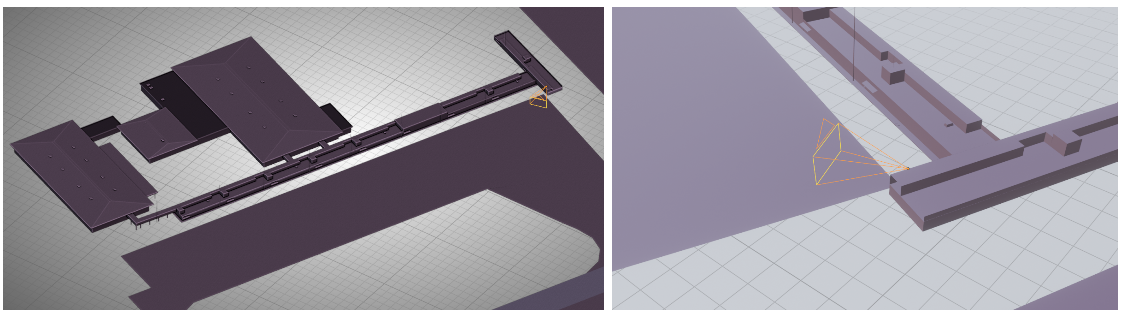
(a) Ground vehicle. (b) Towbar. (c) Passenger bridge.

Figure 3: 3D scene objects for the airport environment.

However, unknown objects could be generated as a random union of geometric primitives and placed in scenes in an arbitrary/targeted manner. In such an analysis, we propose an exclusion procedure that assumes that all detected objects are known and thus operationally belong to the expected factors on the apron. Unknown point cloud clusters are thus automatically considered a source of danger.

We used a total of 338 aircraft models for separate scenes that follow fixed motion patterns implemented by keyframes in Blender. This resulted in a total of 1.690 point clouds, of which we used 1.115 for learning, and 575 again as reference values for accuracy (see Section 3). All the mentioned elements of an airport are combined in Figure 4, exhibiting an exemplary rendering of the experimental airport environment of Singapore Changi Airport. This part of the apron of WSSS served as a reference environment. The different object positions were determined depending on the systematic variation of the distances between the sensor and the target objects.

(a) Airport environment (picture from Google Maps).



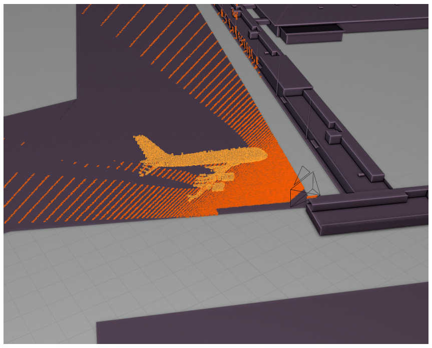
(b) Synthetic 3D scene including a synthetic LiDAR sensor (orange)

Figure 4: Singapore Changi airport environment.

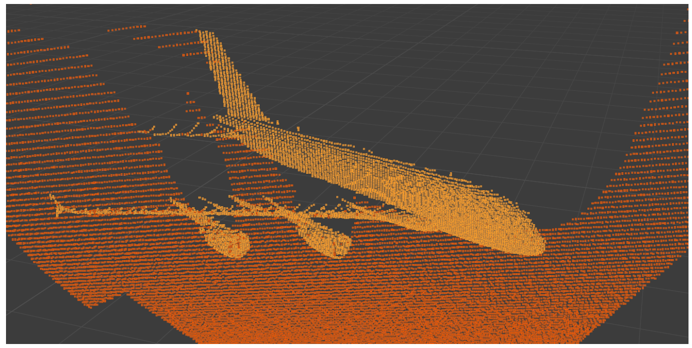
2.2 LiDAR Sensor Simulation

The provided virtual environment enables the generation of synthetic point clouds. Here, the particular characteristics of LiDAR sensor technology have to be considered. In BLAINDER, which is an Blender add-on, LiDAR signals are created with raytracing via intersection points of lines and objects, where *OBBTress* are used to improve computational performance (Zhou et al. 2018). The 3D models from Section 2.1 are integrated in Stanford format (*.stl) or in wavefront format (*.obj, ShapeNetCore).

The implementation in Blender fulfills all requirements for our synthetic sensor approach, i.e. specific materials could be assigned to the models. Further, we added a stochastic noise module to BLAINDER to incorporate inaccuracies and errors, which normally occur in operational environments. This has the task of adding parameterizable measurement inaccuracies and thus, for example, including significant weather situations in the virtual airport environment. We use classical Gaussian noise distribution, which can be individualized by mean value and standard deviation (μ, σ). The following elements are the adjustable parameters of our generic LiDAR sensor or mesh sampling: (a) scan resolution, (b) scan distance, (c) sensor rotation speed, (d) noise μ and noise σ, and (e) reflection. Figure 5 shows an exemplary implementation of a LiDAR scan to detect an aircraft with decreasing density at higher distances and shadowing behind the irradiated object.



(a) Aircraft in the airport scene.



(b) Detail of the sensor feedback.

Figure 5: Synthetic LiDAR sensor feedback in the WSSS airport environment. With growing distance, the density of the emitted rays decreases.

3 MACHINE LEARNING APPROACH

In the application area of machine learning, we use the programming language Python 3.7.3. TensorFlow (Abadi et al. 2016) serves as the machine learning backend, whereby we are aiming for a comparison with other libraries (PyTorch) in future developments. We implemented the given neural networks using the open-source deep-learning library *Keras 2.3.1* (frontend), *scikit-learn* and *Scipy 1.0.0* (routines for numerical integration and optimization). The routines in Section 2.2 are, due to their size not easily accessible, saved via the file format *HDF* (h5py). Training and testing were performed on GPU using CUDA as a parallel computing platform and application programming interface on a NVIDIA DGX-2 AI cluster with 16 NVIDIA Tesla V100 GPUs (performance 2 petaFLOPS), GPU Memory 512GB total, and 1.5TB RAM in a docker container.

3.1 Experimental Setup

As a deep-learning method for classification and semantic segmentation, we chose PointNet++ because it provides better results than comparable approaches and offers advantages, especially for point clouds dealing with non-uniform density through its density adaptive strategy. This corresponds to the challenges of a LiDAR system at an airport with non-uniformly sampled point sets. Our implementation in Keras/TensorFlow has 819.624 trainable parameters and 4.224 non-trainable parameters. Table 1 summarises three different scenarios, which are implemented as test cases for our approach.

Table 1: Scenario definition for investigations on clean and noisy point clouds created from synthetic LiDAR sensor feedback.

scenario	state / noise	description
A	clean	baseline LiDAR sensor feedback
B	Gaussian noise	Degradation of sensor performance (e.g., in bad weather conditions)
C	clean	violation of safety clearances

These three scenarios are used as proof of concept. Scenario A serves as a reference case to evaluate a baseline to be achieved by optimal feedback derived from a LiDAR sensor (ray tracing). In the second scenario (B), we have implemented a Gaussian noise that affects the sensor feedback. Here, the feedback is incomplete and also shows erroneous feedback. These can occur in operational environments, e.g., due to high humidity (rain). From our perspective, this specific case represents a very good application opportunity for the use of AI methods. In the virtual environment, ground truth information is available at any time and a wrong assignment can be detected. This point, in particular, cannot be guaranteed in the real environment and requires manual intervention, which in turn significantly reduces the amount of input data compared to an automated training process. Scenario C is the first investigation of whether a violation of safety clearances can be detected (incidents, potential conflicts) within a fully classified scene with a reasonable effort.

3.2 Results

As a result of the investigation a strong interaction between segmentation and classification is observed. In the first step of the investigation, the raw point clouds were separated into distinct areas. This works well for the airport apron scenes because the background (surface) is homogeneous. This allows individual objects, such as aircraft or service vehicles, to be separated very well. The resulting geometric appearance of these objects is easy to interpret and can be assigned well using the object database.

Table 2 contains the results of the accuracies (correctly assigned points to an object group). Whereas large objects, such as aircraft or airport buildings, could be classified with a high level of accuracy, the accuracy for mid-sized objects (finger, ground vehicles) decreases by approximately 10% and by another 10% for small objects. These results (scenario A) are comparable to the results provided by Qi et al. (2017). The implementation of the Gaussian noise results in a degraded accuracy, which is particularly problematic for the case of (mobile) ground vehicles (accuracy drops by 27%). The classification accuracy for boarding bridges (finger) is also significantly affected, but these are infrastructure elements and will be static in relation to the final sensor position.

Table 2: Mean accuracies of semantic segmentation of scene objects.

Scenario	A	B	offset
Accuracy (%)	75.4	66.7	-12 %
1 - aircraft	81.2	76.8	-5 %
2 - airport buildings	84.7	81.0	-4 %
3 - finger (boarding bridge)	73.3	62.1	-15 %
4 - ground vehicles	75.0	54.8	-27 %
5 - apron misc	63.0	58.6	-7 %

Aircraft are classified at a high level of accuracy, even under the degraded performance of the LiDAR sensor. We expect that additional data about aircraft position or type, as provided by ADS-B messages (cf. Schultz et al. (2022)), will improve our results. We have modeled a realistic behavior of LiDAR sensors by generating deviations of the sensor feedback due to dropout and noise. To further improve the realistic sensor feedback and mitigate the effects of perturbations, the next step should be to investigate suitable compensation strategies, such as an autoencoder with PointNet as encoder and a fully connected decoder. This approach could counteract the expected high impact of severe weather situations by learning to reconstruct the original signal. The implementation of alternative approaches such as FoldingNet (Yang et al. 2018) should also be considered to analyze the capabilities and limitations of the different signal reconstruction methods.

Figure 6 shows the dependencies of the model accuracy when the pose of an aircraft changes (rotation around z-axis, 0 means objected is heading to the sensor). The curves exhibit a significant drop in accuracy at particular observation angles, which must be considered when looking for an appropriate sensor location.

Scenario C includes the detection of safety distance violations. Here, bounding boxes are created around segmented point clouds (see Figure 7) and checked if they have overlapping areas. These bounding boxes are generated by the maximum extensions of the point cloud (maximum Euclidean distance of two points within a segmented set).

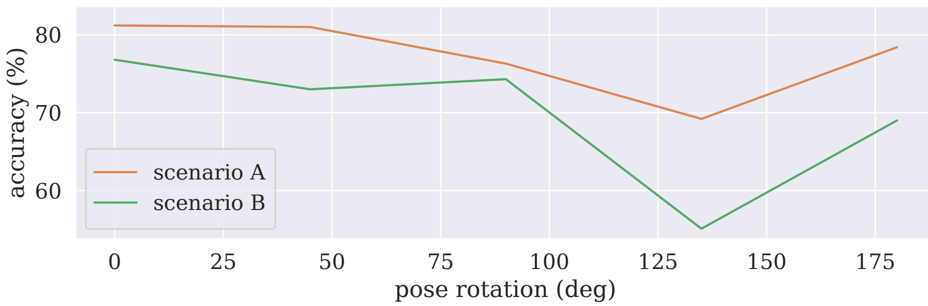


Figure 6: Model accuracy considering different pose rotations with aircraft as target object.

If these boxes overlap, an incident is detected, which needs the attention of the apron operator. This simplified approach could already make a significant contribution to the airport safety net. It should be noted, of course, that quality of conflict detection is closely related to the accuracy of semantic segmentation and the quality of sensor feedback.

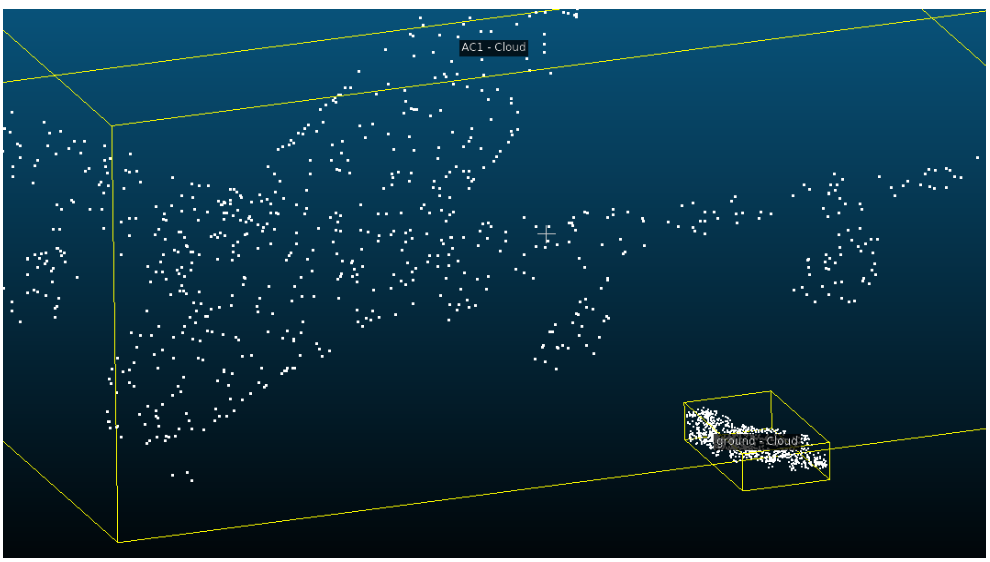


Figure 7: Detection of safety distance violations by identifying overlapping bounding boxes around segmented point clouds.

4 CONCLUSION AND OUTLOOK

In our prototypical example, we have focused on an implementation of a synthetic LiDAR sensor in a virtual airport environment. We used Singapore Changi Airport since we are experienced with the operational environment and environmental conditions. The aim of the paper, and also of our ongoing research, is the semantic segmentation and classification of the raw point clouds captured by LiDAR sensors in a virtual airport environment. These point clouds could provide an additional contribution to increasing safety by supporting apron controllers. Although a performance comparison between actual controller performance with and without a sensor-supported environment is not available, we strongly believe that our approach will improve apron surveillance, especially under severe weather conditions.

The availability of sufficient and high-quality data for the training of deep learning algorithms is still problematic, but necessary for the automatic evaluation of the point clouds. In our example, we have decided to use the proven PointNet++ and have generated and provided data synthetically using a sandbox-like approach. We propose a first experimental investigation and aim to automate the whole process chain to adaptively generate data for arbitrary airports and prepare deep learning methods for real-world applications. While the airport infrastructure can be generated easily from free geodata (e.g., OpenStreetMap) and repeating individual elements (ground vehicles, fingers, etc.) into three-dimensional models, the sensor technology must correspond to the characteristics of the systems used at the respective airport. In our approach, we are using parameterizable sensor modules (LiDAR) implemented in BLAINDER, which can be calibrated according to actual system requirements. In further scientific investigations, the physical effects of the objects' materials (e.g., glass) must also be taken into account to a greater extent in order to avoid a subsequent artificial deterioration of the point cloud quality through stochastic noise and to integrate this directly into the sampling process.

For aircraft, ShapeNetCore provides a sufficient and high-quality data foundation. This includes 338 models and a wide range of shapes and differences. However, especially in the area of aircraft, we see further potential in the analysis of point clouds. While in this paper we focused exclusively on the separation of aircraft and other airport elements, Deep Learning can also be used for pose estimation and type recognition. By correlating with position data (ADS-B), highly complex, automatic, and adaptive models for apron control can be trained and directly transferred to real-life operations. While our previous approach focused on static point clouds, we would like to gain knowledge about variable objects and their interaction on the apron. The code will be made freely available after the completion of the investigations. We also strive for visualization in a suitable virtual reality environment (Cave Automatic Virtual Environment) to combine this approach with enhanced tower concepts to be developed in close cooperation between Bundeswehr University Munich, TU Freiberg, and ATMRI at NTU Singapore.

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AUTHOR BIOGRAPHIES

MICHAEL SCHULTZ is Full Professor and holds the Chair of the Air Traffic Concepts at Universität der Bundeswehr München. He received a Diploma degree in business and engineering, a Ph.D. degree in logistics and aviation technologies, and a Habilitation degree in aviation from Technische Universität Dresden, Germany, in 2002, 2010, and 2019, respectively. He is Visiting Researcher with the Air Traffic Management Research Institute, Nanyang Technological University, Singapore. His research interests include data-driven and model-based approaches to improving air transportation, flow-centric airspace management, inter-airport coordination, performance-based airport and aircraft operations, and advanced concepts for future traffic management. Prof. Schultz is an Editorial Board Member of Transportation Research Part C: Emerging Technologies and the Section Editor-in-Chief of Air Traffic and Transportation —- A Section of Aerospace. His e-mail address is michael.schultz@unibw.de. His website is https://www.unibw.de/lvk.

STEFAN REITMANN is a postdoctoral researcher at the Institute of Computer Science at the Freiberg University of Mining and Technology. In 2020 he received his Ph.D. at the Dresden University of Technology in the field of applied machine learning in time series forecasting. During his Ph.D. phase, he was part of the scientific exchange program of the German-Russian Interdisciplinary Science Center (G-RISC) and stayed at the State University St. Petersburg (SPbU) in 2016 and 2017. Associated with this research he received the Young Russian-German Scientist Award in 2016, the best paper award of ICRAT in 2018, and the best paper of track award at ATM Seminar in 2019. In 2015 he received his diploma in Traffic Engineering at the Dresden University of Technology with a focus on traffic flow sciences. His research focus is on machine learning and computer vision. Dr. Reitmann is currently working on analyzing point cloud data with neural networks. His e-mail address is stefan.reitmann@informatik.tu-freiberg.de.

BERNHARD JUNG holds the chair for Virtual Reality and Multimedia at the Institute of Computer Science, Freiberg University of Mining and Technology. He studied computer science and computer linguistics at the University of Stuttgart, Germany, and the University of Missouri, Saint Louis. He received his doctorate degree in 1996 from the University of Bielefeld with a thesis on dynamic knowledge representation as well as a Habilitation degree in 2002 for a thesis on intelligent virtual environments. From 2003 to 2005 he was Full Professor for Media Informatics at University of Lübeck's International School of New Media. Prof. Jung's research interests are in the fields of Virtual Reality, Large Data Visualization, Human-Computer Interaction, and Advanced Robotics. His e-mail address is jung@informatik.tu-freiberg.de.

SAMEER ALAM received a Ph.D. degree in computer science with a specialization in artificial intelligence from the University of New South Wales (UNSW), Australia, in 2008. He is currently an Associate Professor at the School of Mechanical and Aerospace Engineering, Nanyang Technological University (NTU), Singapore, where he is also the Deputy Director of the Air Traffic Management Research Institute (ATMRI). His research interests include machine learning, computer vision, multi-agent systems, applied to air traffic, and airport operations. Prof. Alam is an Editorial Board Member of Transportation Research Part C: Emerging Technologies. His e-mail address is sameeralam@ntu.edu.sg. His website is https://dr.ntu.edu.sg/cris/rp/rp00160.