

LiDAR processing

Automatic point clouds classification

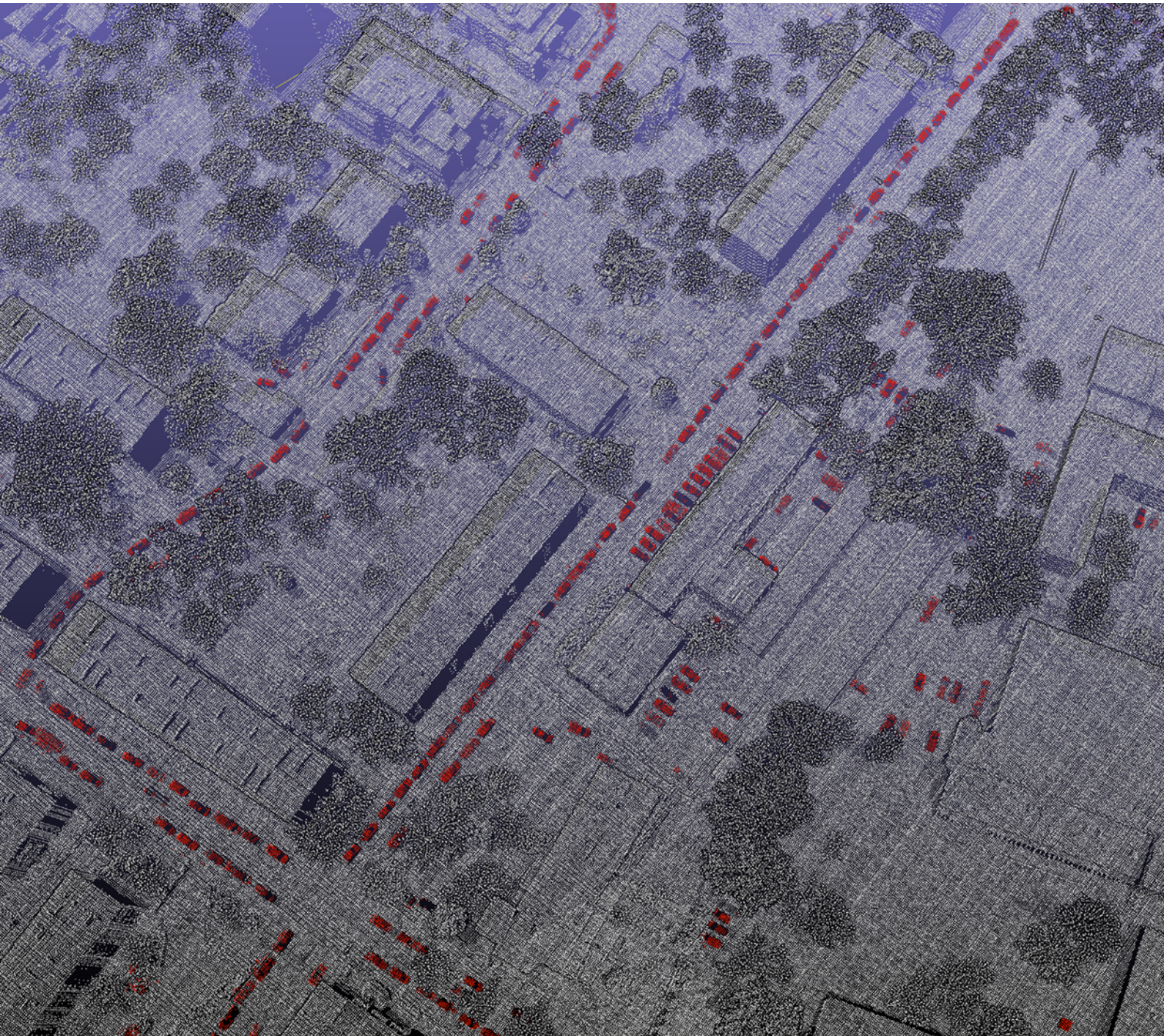




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OPEGIEKA's experience in automatic classification

Introduction

The following report explains the method of automatic point clouds classification that has been used by OPEGIEKA during the execution of several projects since 2019. Its strengths, flaws and future potential had been described.

The method has been developed by OPEGIEKA's engineers as a result of R&D works executed using the company's own aircraft, remote sensing devices as well as in-house developed software and solutions commonly available on the market.

Sharing that experiences and knowledge is our way of taking a stand in a current discussion about the future of manual work in processing the remote sensing data. In OPEGIEKA we stongly believe in automating the processes of data analysis.

The details of the most recent project in which the method was successfully launched are presented below. The data was gathered during the execution of the CAPAP project in Poland.



EXECUTION PERIOD:
May - June 2020



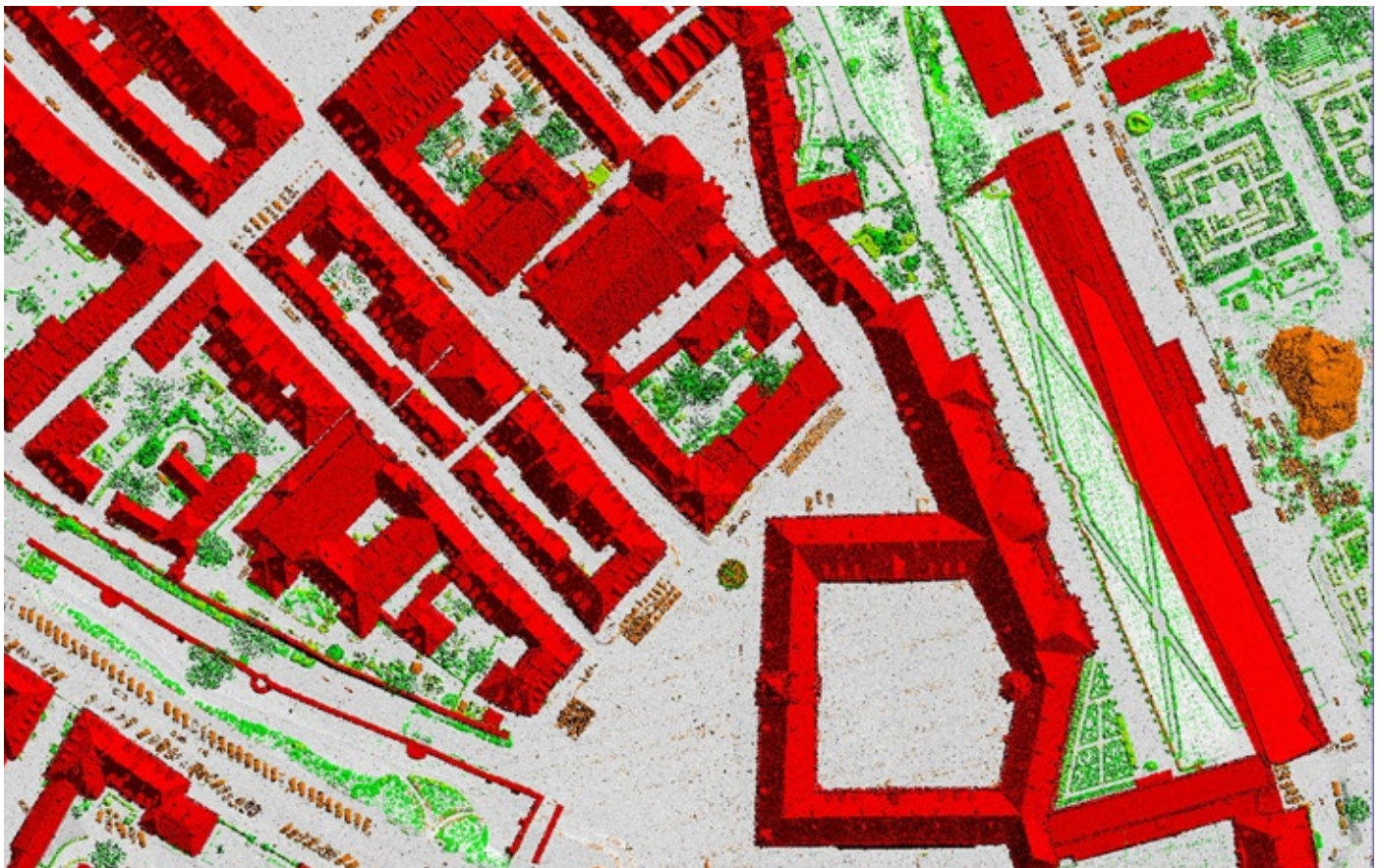
DENSITY:
12 pts per square metre



TERRAIN TYPE:
Lubusz Voivodeship
(mostly plain terrain)



COVERAGE AREA:
745 square kilometres



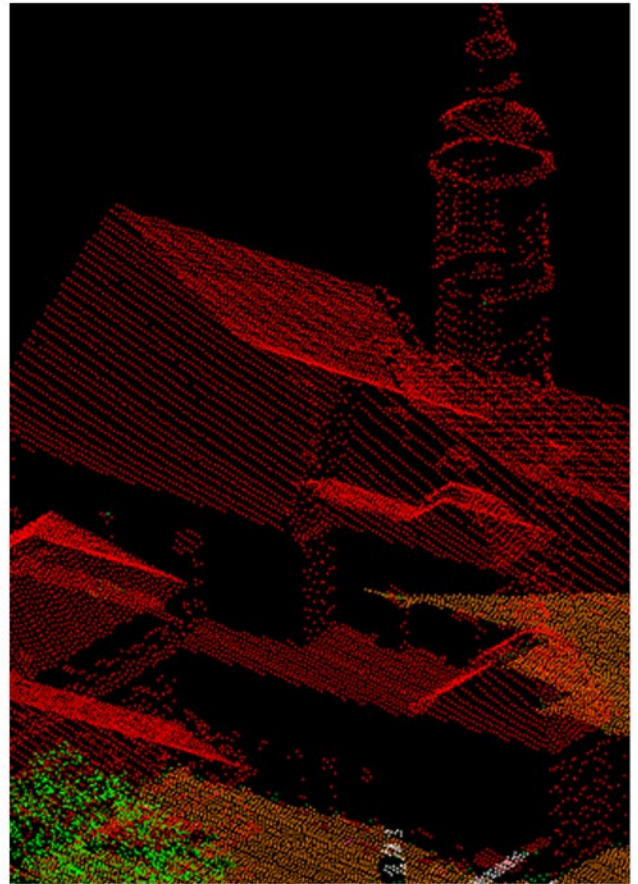
PART I - METHODOLOGY OF THE CLASSIFICATION

Workflow

OPEGIEKA's solution for point clouds classification is based on fully convolutional neural network. The core of the solution is the in-house developed algorithm of point cloud transformation to regular array accompanied by internally designed convolutional neural network architecture. The network uses only the X, Y, Z coordinates of the point cloud. Additional parameters of the points such as intensity, return number and number of returns for a given pulse can be used optionally. The required inputs consist of point clouds divided into tiles in *.las format and a vector file containing tile definition. Firstly, point clouds are transformed into a form suitable for a convolutional neural network. Then, the output of the neural network is transformed back into point cloud form. The returned *.las files are identical to the input ones with predicted classification being the only difference.

In order to carry out point cloud classification the neural network has to be trained using correctly classified data sample. The training sample should be classified according to the target class definition for the data to be classified. It is important that the classification of the training sample is consistent and as accurate as possible, so that the neural network will avoid learning errors or misinterpreting the results.

For each project a training sample has to be selected and classified with the highest accuracy. The required amount of training data depends on the terrain type. For a LiDAR block representing a homogeneous terrain type a few square kilometres of representative data would be enough. If the terrain type varies, the optimal results



are obtained by training dedicated models for different terrain types, such as urban, rural, forest, seacoast, flat, mountainous.

The process of training the neural network from scratch takes a couple of days. When training models dedicated for different terrain types a pretrained general model can be used which reduces the amount of time required for training further models. Furthermore, model trained from another project can be used as a pretrained model as well. However, if the number of classes is different retraining the model will take longer, causing the drop of significance of the amount of time saved in comparison with identical class definition.

After training the neural network, the classification of the point cloud is carried out by prediction of the neural network. For practical reasons the LiDAR data is divided to 500 by 500 metres tiles.

The full process of classification of such tile takes about 3-4 minutes on a single machine equipped with a graphic card (GPU).

In order to obtain optimal results an automatic cleaning of the classification obtained from the neural network is carried out. That means applying a set of Terrascan macros, enabling for deleting some of classification errors of insignificant importance to the statistic accuracy, but decreasing the visual quality of the classification. The core of this stage is applying several macros based on an isolated points and point neighbourhood analysis.

applying the method enables for achieving a significant reduction of time required to dedicate for manual inspection and increasing the final quality of the classification

At the final stage the point cloud is subjected to manual inspection to correct residual errors and objects that require human interpretation.

Suitability

The proposed solution allows to minimise the amount of manual work in comparison with conventional methods applied before that are based only on the Terrascan macros. The advantages of OPEGIEKA's method are the most clearly visible on objects difficult or impossible to classify using state of the art automatic methods, such as cars, building walls and details, powerlines etc.

The company's experience shows that applying the method based on neural network enables for achieving a significant reduction of time required to dedicate for manual inspection, as well as increasing the final quality of the classification. Those are main reasons making OPEGIEKA's engineers believe this is the best methodology at the moment.

Limitations

The method requires having a correctly classified sample data of the size of at least a few square kilometres. The sample is used as a training data for the neural network. Consequently, the quality of the classification of the training data is crucial for the accuracy of the latter automatic classification. Moreover, the training data has to be representative for the data to be classified. It has to contain all types of objects that occur in the project area in a representative quantity. Therefore, the training samples have to be carefully selected from the whole dataset. This is an additional difficulty of the whole classification process compared to the conventional workflow.

To obtain optimal results the training data has to come from the same project. This requires a reorganisation of the classification workflow. Firstly, some samples of a representative data has to be classified correctly. Then, the training process, which takes a few days, is carried out. Necessity of spending that additional time is an important drawback of the workflow.

PART II - CASE STUDY: THE CAPAP PROJECT

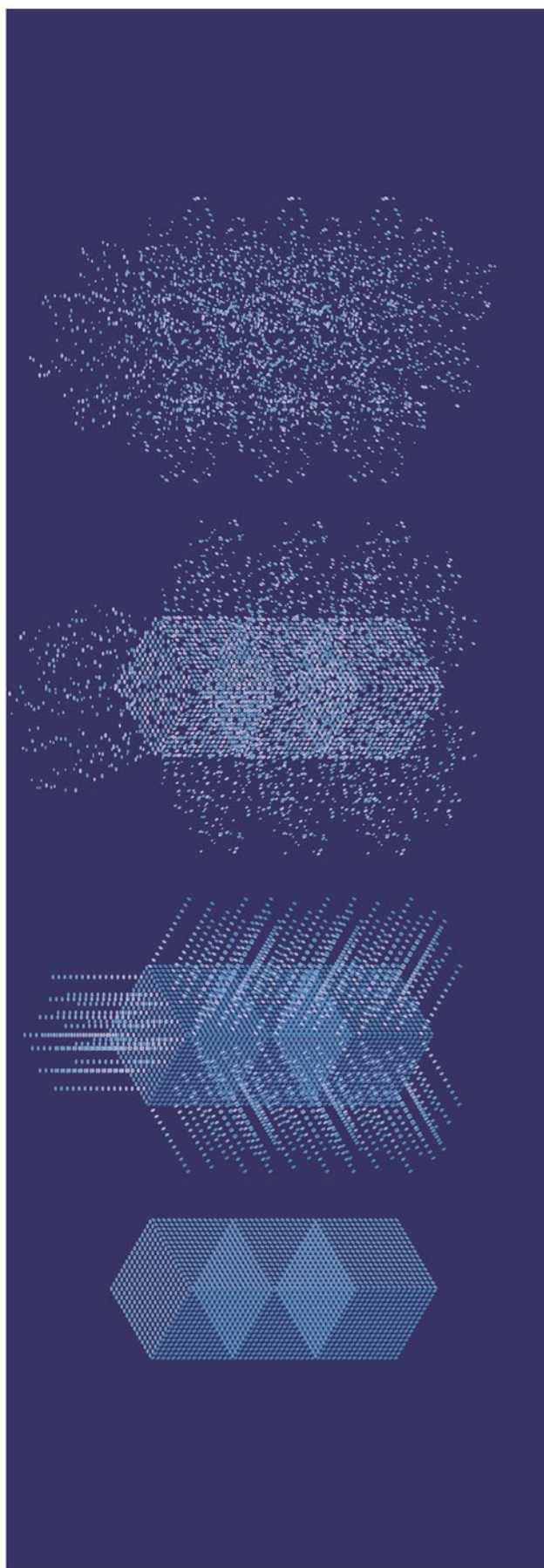
About the project

The Centre for Spatial Analysis of Public Administration (CAPAP) is the project that has been implemented in Poland by the Head Office of Geodesy and Cartography (GUGiK) since 2015. The CAPAP aims at carrying out tasks concerning creating modern centre of spatial data, which would boost the analytical capacity of Polish public administration. Its main goal is to increase the range of exploiting the spatial data by citizens, entrepreneurs and public administration entities and it is greatly focused on, but not limited to, 3D data and digital maps adjusted to the purpose of carrying out the spatial analysis. OPEGIEKA has been involved in the project implementation since the beginning by gathering and processing both LiDAR data and aerial imagery from the different parts of the country.

Implementation process

The current automation method was implemented for the first time during the execution of the CAPAP project in 2019. In this case, the entry dataset required for conducting the training has been selected manually from the vicinity of Balice and Warsaw. The data sample consisted of nearly 1000 sections, with single section being a square with side length equal to 500 metres. The values used for prediction in the CAPAP 2019 had been obtained after a few days of training the model. As a matter of fact, already then it has been noticed that using automation in such project could lead to achieving satisfying results. For further optimisation of the process, the approach towards the training and class distribution has been changed. In the CAPAP project a few types of objects that differ with respect to their shape and spatial position were contained within a single class. In order to simplify the learning process of the machine, the new class division has been created, which allowed for more complex segmentation, i.e. cars,





staircases, terraces, powerlines and so on had been allocated separately. Subsequently, a few representative, urban sections had been selected and manually prepared as an entry data for the training on previously changed classes. It is worth mentioning that the highest possible quality of the entry dataset consisted of manually prepared sections is essential. Due to that approach a few sections were created, which the neural network had been trained on. The abovementioned process of the optimisation has led to expected effects resulting in greater accuracy of the classified objects.

Making the difference

Substantial advantage of implementing the automation processes in the CAPAP is achieving the high level of data coherence, which is especially difficult to accomplish using only manual methods. Apart from this, the increase in the accuracy of classifying points allocated for the objects that the model has already been familiar with was observed. Besides, the acceleration of the data processing was equally important. The best results have been observed within the urban area, where typical objects occur commonly, e.g. detached houses or cars. In such cases, the increase of the efficiency amounted to several dozens of percent. In general, the prediction time for a single section characterised by size 500 per 500 metres and density of 12pts per square metre lasted approximately 2 minutes. Admittedly, the developed technology has great potential for optimisation. Due to that fact, the company is going to carry out the works regarding further improvements leading to even more accurate classification of the irregular objects.



PART III - OPEGIEKA'S experience

OPEGIEKA Sp. z o.o. has been active on geospatial market since its establishment in 1989. Initially, the company's business activity was closely related to execution of standard geodetic and cartographic services. Access to advanced technologies and drive for development caused that it quickly started gaining experience in new activities and introduced new services to their product portfolio.

In 2002, OPEGIEKA started investing in photogrammetry, aerial imagery processing and production of orthophotomaps. Since 2010 they have been operating own aerial survey equipment.

Currently the company possess three photogrammetric aircraft, two large-format

and two medium-format aerial cameras, thermal camera and three remote sensing laser scanners.

OPEGIEKA's experience in automatic point cloud classification is based on:

- its background in using state of the art geometrical approaches (mostly based on Terrascan and their own software), as well as knowledge of the employees, some of whom have been working in this field for more than 20 years;
- research on deep learning approaches for automatic point cloud classification, which the company started in 2016.

It should be also emphasised that having own data centre, which allows for flexible scaling of the processes associated with data processing, has indubitably a beneficial impact on the team's productivity potential.

Nature and origin of the point clouds

OPEGIEKA focus on point clouds captured by remote sensing equipment from either aircraft or helicopters. For internal use, the company processes data captured by one of 3 RIEGL scanners it owns: VQ-1560 II, VQ 1560i-DW and LMS Q680i). It also had tested their deep learning solution using data derived from RIEGL Vux and Leica SPL (in limited scope).

Automatic detection of the object classes

For current needs the company usually applies in-house developed automated methods of classifying point clouds to the following groups: ground surface, vegetation, buildings and bridges, water surface, noise

```
conv2d.transpose(4 * mwk, (2,2), stride
concatenate([u7, c1])
Conv2D(4 * mwk, (2,2), padding='same
BatchNormalization()(c7)
= Activation(activation='relu')(c7)
= Conv2D(4 * mwk, (2,2), padding='s
= BatchNormalization()(c7)
7 = Activation(activation='relu')(c
outputs = Conv2D(n_class, (2, 2),
def weightedLossFunction(y_true
weights= tf.convert_to_tens
loss = tf.reduce_mean(-tf.
return loss
7
68 model = Model(inputs = [inp
69 model.compile(optimizer =
```

above and below ground, all other manmade objects that are not buildings nor bridges (vehicles, fences, powerlines, power poles, street lanterns, bus stops, temporary ground repository, greenhouses, jetties etc.) and other commonly used classes.

OPEGIEKA had tested and obtained outstanding results with classifying objects like vehicles, building facades, stone walls on the fields, etc. as a separate classes

However OPEGIEKA's experience shows that automatically performing more detailed classification is feasible. The general rule is that if a type of object is clearly and logically distinguishable from the point cloud basing only on point cloud geometry (without any external source of information or a general knowledge about the world that is inaccessible for the machine learning algorithm) it can be automatically detected with the use of described methods.

The company had tested and obtained outstanding results with classifying objects such as vehicles, building facades, stone walls on the fields, etc. to separate classes. The solution is flexible and allows for defining any number of classes to be classified.

The only requirement is to have training data of good quality where the objects to detect are correctly classified as a separate classes.

Quality of the classification

The quality of automatic classification of the point cloud is difficult to measure statistically. The percentage of correctly classified points does not always reflect the quantity of work that has to be done in order to achieve fully correct classification. It depends on the distribution of the misclassified points and the number of objects requiring manual correction of the classification. In the results obtained with the use of our methods the majority of objects that usually are subject of a human intervention, such as buildings and vehicles, are classified correctly. The most commonly, errors are related to rarely occurring or unconventional objects that “confuse” the neural network leading to mixing different classes. However, if this type of objects is concerned, avoiding human intervention is nearly unattainable. The number of such objects is insignificant, therefore the need of human intervention is greatly reduced in comparison with conventional methods.

The statistic accuracy depends on many factors and vary greatly from tile to tile depending on the objects that occur on a given tile. In order to present possibly the most objective statistics the company used the results obtained at the ISPRS 3D semantic labelling benchmark (<https://bit.ly/3cJ1AzR>). Achieved results place OPEGIEKA in the top 3 of the classification accuracy rating. It is worth mentioning that most of the authors use external tool for ground classification and use this information as an input to their algorithm. However, OPEGIEKA's method uses only the information obtained directly from the las files, such as points coordinates and intensity (optional), return number and number of returns for a given pulse. The company claims that efficiency is big advantage of their method, as it takes less

than 60 seconds to classify the reference dataset of the benchmark.

The statistical results achieved with the use of OPEGIEKA's methods:



POWERLINE
F1-score: 50.4



LOW VEGETATION
F1-score: 81.3



IMPERVIOUS SURFACES
F1-score: 91.1



CAR
F1-score: 77.0



FENCE/HEDGE
F1-score: 27.9



ROOF
F1-score: 93.2



FACADE
F1-score: 56.0



SHRUB
F1-score: 41.2



TREE
F1-score: 80.1



OVERALL ACCURACY
F1-score: 82.6

It is worth emphasising that the dataset given in the benchmark is limited and results presented above do not correspond to the efficiency of the method in real-life conditions. When conducting actual projects, the method usually enables for achieving more than 95% of accuracy on classes like ground, buildings and unclassified which are crucial for the amount of manual work required.



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