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THE USAGE OF GEOSPATIAL TOOLS IN TRAFFIC SIGN DETECTION

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ABSTRACT

The topic of this scientific paper is the detection of traffic signs based on the data obtained using modern geodetic methods (LiDAR, mobile laser scanning), by using geospatial tools. In a total of 100 photos taken in an urban area in Germany, in a length of 500 m, 75 traffic signs were detected. Each sign is assigned a corresponding code from the catalog of German traffic signs, after what the photos are connected to the point cloud. Then the extraction of bounding boxes and central points of traffic signs was done. The visualization was done in two softwares - Bentley MicroStation and QGIS, which completed the detection process. The accuracy of traffic sign detection in photos is 83% (62/75). The extraction of bounding boxes and central points on the point cloud was performed with a high degree of accuracy (85%).

Keywords: *traffic sign detection, geospatial tools, geodesy, geoinformatics*

INTRODUCTION

Traffic signs are used to regulate traffic, warn road users of danger and provide useful information, all with the aim of increasing the safety of road users. The existence of a unique list of traffic signs with their locations is very important for traffic safety, but also for the needs of driving-assistance systems and autonomous vehicles. In conditions of reduced visibility on the roads, the computer vision of the vehicle can help the driver in detecting traffic signs and reduce the risk of traffic accidents. In autonomous vehicles, it is also crucial to develop real-time sign detection to make driving as safe as possible and autonomous vehicle reactions as fast and adequate as possible (Fang, Chen, Fuh, 2003; Jensen, Nasrollahi, Moeslund, 2017).

The data used in this paper refers to the detection of traffic signs in Germany. All traffic signs in Germany are classified into warning signs, regulatory signs, informatory signs and additional signs. They are usually placed on the right side of the road next to the carriageway (Straßenverkehrs-Ordnung (StVO)).

One of the widely used modern methods for collecting spatial data is the LiDAR (Light Detection and Ranging) method, which measures the distance to an object based on a laser scanner. In this paper, the focus will be on Mobile Laser Scanning (MLS), as it was used to acquire the data.

Along with the improvement of methods for collecting and processing data, information systems, computers and electronics were being developed. The use of artificial intelligence (AI) in data processing stands

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out among the most modern trends in geodesy and geoinformatics (Ma et al., 2019). Specifically, in geoinformatics and geodesy, AI is used to speed up various processes, optimize complex measurements, analyze deformations, navigation, etc. (Reiterer et al., 2010). AI is intensively developed for the purposes of analyzing and detecting objects of interest in photos - road damage (Davidović, Vasić, Batilović, 2020), traffic signs (Houben et al., 2013; Fang, Chen, Fuh, 2003) etc. As traffic sign detection technology is mostly used for the needs of autonomous vehicles, the literature in this area was also used. The geographic aspect of autonomous vehicles is that these vehicles use LiDAR and GPS technology, and as they advance and become more widely distributed, new spatial data will be collected and processed on a daily basis.

The subject of this scientific paper are traffic signs and the process of their detection using various geospatial tools. The goal is to show the application of geospatial tools in the detection of traffic signs on the concrete example of a scanned area in Germany. The task consists of several steps: data collection, initial data processing, point cloud registration, point cloud classification, traffic sign detection.

In the next part of the paper, analyzed scientific papers dealing with topics related to the topic of the paper will be presented, then the used methods, the results of the paper, the discussion, as well as the conclusion at the end of the paper.

OVERVIEW OF PREVIOUS RESEARCH

This chapter will give a brief overview of scientific papers that deal with the research of new geodetic technologies and works that have the detection of traffic signs as their topic.

LiDAR, that is MLS, play a major role in the collection of spatial data of road infrastructure. Modern technologies have enabled fast, easy and efficient data collection, and the point cloud on which the extraction is performed is clearly visible and detailed. Because of this, the extraction of necessary elements can be performed precisely, with minimal errors (Vasić et al., 2018). This research has shown how MLS has facilitated the collection of data and how detailed that data actually is, and that it can be applied in various areas that use road infrastructure data.

There are many methods of detecting traffic signs in photos. Salti et al. (2015) use two algorithms to extract regions of interest, the first of which detects strong contrast regions (MSER) and the second detects symmetric regions (WaDe). Traffic sign detection is then carried out in the selected regions based on color analysis in the region. German traffic signs were used to train the software, and then detection was performed on Italian signs. The detection accuracy for German traffic signs exceeded 98%, while for Italian it varied from 72% to 82%, depending on the type of signs. At the end of the paper, the further development of this method and the improvement of the quality of photographs are suggested, for more accurate detection. Another paper similar (Houben et al., 2013) uses three real-time sign detection algorithms. A dataset of 600 images was used to train the software. One of the algorithms gave 98.8% accuracy for regulation signs, but 67.3% for informatory signs, but the other two algorithms performed worse. In conclusion, it is necessary to improve the algorithms, but also to apply different algorithms for different classes of signs.

Another paper that deals with the application of different algorithms on photographs in order to detect traffic signs is Belaroussi et al. (2010). Two of the three algorithms use pixel color for detection, and the third compares the relationships and similarities between pixels. The accuracies of these three algorithms were compared on a data set of 847 images, on which there were 251 traffic signs. On photos where the signs are far from the camera, all three algorithms show a detection accuracy of 71% to 73%. In photos where the signs are closer, the detection accuracy is 97% for the algorithms using pixel color and 100% for the third algorithm. A big problem is also wrongly detected signs, especially when they are far away in photos. In conclusion, the authors state that the accuracy of detection on distant signs should be improved and the occurrence of false detections - occurrences when the wrong object is recognized instead of the right one - should be reduced.

Weather conditions have a great influence on the ability to collect data with LiDAR and cameras. Four scientists (Zhang et al., 2023) studied the influence of different weather conditions (rain, fog, snow, smog) and their intensities on the operation of eight different sensors, including LiDAR and camera. The influence of weather affects these two sensors with almost equal intensity - in conditions of heavy rain and dense fog they cannot be used. The biggest difference is that LiDAR cannot be used in snowfall, while a camera can with certain limitations. This is very important for autonomous vehicles, considering that rain increases the risk of traffic accidents by as much as 70%. Various computer tests determined that the solution could be to use several different sensors in autonomous vehicles, which have different resistance to certain weather conditions. In addition, it is possible to fill in the scan gaps using AI. The authors are hopeful for a bright future for sensor and autonomous vehicle research, given the rapid advancement of technology.

The problems that arise in the detection of traffic signs by autonomous vehicles are the speed and accuracy of detection. It is necessary to accurately detect signs in real time. Most algorithms rely more on one or the other problem, while it is very difficult to achieve both. Li, Li, Meng (2023) propose an improved Attention-YOLOV4 (You Only Look Once) method, based on convolutional neural networks (CNN), similar to the one used in character detection in this thesis. For the training of CNN 6105 photos were used, while the algorithm was tested on 3071 photos. They compared the detection results between their algorithm and four other algorithms. Of the five methods, two are faster than the proposed method, but the detection accuracy (about 85% on average) is far higher than the accuracy of the fastest method (by 6-25%). Although this method represents a good balance between accuracy and speed, the authors believe that there is still room for improvement of detection accuracy.

In addition to this set of analyzed scientific papers, many more have been written on the subject of modern geodetic methods, traffic sign detection, as well as on autonomous vehicles and their detection systems. The conclusion of each of these works is that all methods can be further developed, in order to improve the speed of data collection, accuracy and precision of the obtained results. This scientific work will be another step in the analysis of the three mentioned topics and will contribute by applying the previous knowledge on examples from practice.

MATERIALS AND METHODS OF RESEARCH

In the writing of this scientific paper, data obtained by 3D laser scanning - LiDAR on the terrestrial platform (mobile laser scanning) were used, and then processed in several different softwares and stages. In this chapter, an overview of LiDAR and all phases of work will be given.

LiDAR (Light Detection And Ranging) is an active remote sensing technology for measuring the distance of objects. With the development of platforms as carriers for LiDAR comes the development of mobile laser scanning (MLS), which was used to collect the data for this work.

The MLS system consists of four basic components: a laser, an INS/IMU (Inertial Measurement Unit/Inertial Navigation System) unit, a GNSS (Global Navigation Satellite System) and a data storage computer (Figure 1). Optional components are also distance measure indicators (DMI), which measure tire rotation, indirectly giving an estimate of distance traveled (Olsen et al., 2013). All these components enable the rapid collection of a large amount of precise data.

As a result of LiDAR scanning, a point cloud is obtained - 3D positions of a network of points that cover the scanning area (Vasić, 2017). It is most often saved in .las format, which can then be loaded and processed in specialized software (PointTools, MicroStation, ArcGIS, AutoCAD...).

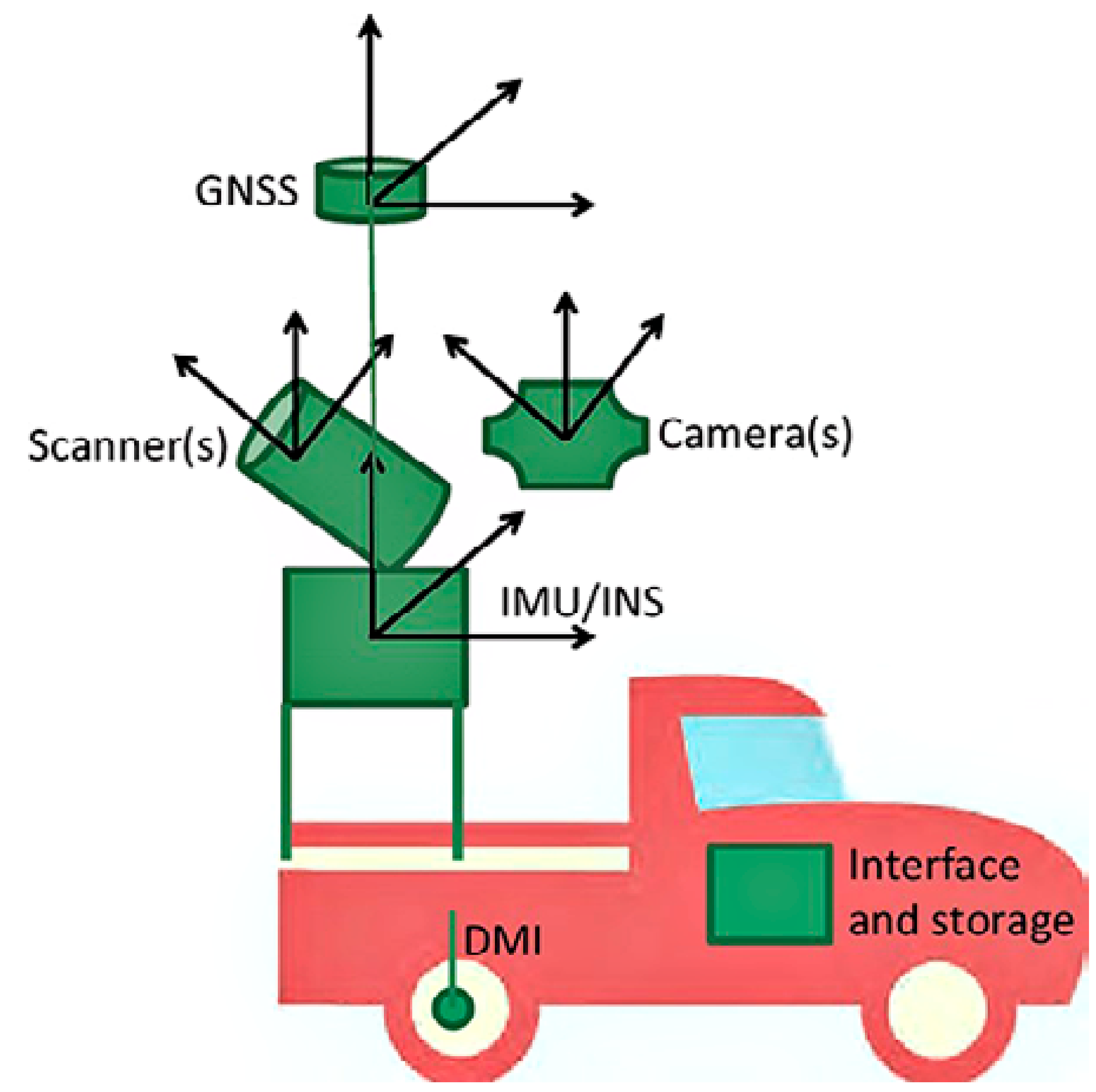

Figure 1. Components of MLS
Source: Olsen et al., 2013.

The collection of data used in this work was carried out with a Trimble MX9 device in Germany during the year 2022, and then the data was further processed. The device specifications are as follows:

- Precision: 5 mm
- Maximum scanning speed: 2.000.000 points/s
- Camera resolution: 30 MP

INITIAL DATA PROCESSING

Initial processing includes the processing of raw (.las) data obtained from the vehicle that was recording the point cloud, as well as the acquisition of panoramic and planar images of the traffic route of interest.

APPLANIX POSPac MMS® (POSPac) software recalculates and corrects the vehicle's trajectory for a certain period of time, as well as transforms it into the desired coordinate system and date. Based on corrections from permanent stations/virtual stations, a corrected trajectory of the vehicle's movement is obtained.

Using another software tool - Trimble Business Center (TBC) - a point cloud is generated/plotted for the surveyed area. In addition, a spatial and height check of the coincidence of the generated point cloud with photographic (panoramic and planar) images of the road route is carried out, since the cloud is georeferenced, as are the photographs.

Orbit Content Center is used as the third software tool and it serves to optimize the data set obtained by the previous tool in order to publish it on the Internet browser. Optimization also means adjusting the data set for use on the Internet browser, without interruptions, difficulties in loading, manipulation and viewing.

For legal reasons, it is necessary to blur the license plates of vehicles and the faces of pedestrians, so the taken photos are blurred by the automatic blurring tool. After blurring and optimizing the recordings, the data sets are uploaded to the Internet and the data can be accessed by users via an Internet browser.

POINT CLOUD REGISTRATION

Point cloud registration involves determining precise links between two or more sets of data, which were obtained by recording the same space on several occasions, from different angles or using different sensors or platforms. Bentley MicroStation software and the TerraMatch extension were used for point cloud registration.

The first step in point cloud registration is to get all the raw point clouds that were created in the capture – from each pass and from each scanner individually. These point clouds have different positions and their deviations can vary from a few millimeters to several meters (Figure 2). In order for any project to be done as precisely as possible, it is necessary to reduce the deviations in cloud coordinates as much as possible (Vasić et al., 2019a). There are two types of registration - relative and absolute.

Relative registration represents the matching of all point clouds to each other. This is done using two tools. The first tool is used for correcting to the cloud position. By locating specific details and placing points at the same location on all point clouds (tie lines), the software calculates relationships between marked locations. When a large number of locations on the point cloud are flagged, a repair is made for that entire part of the cloud. The second tool is used for height corrections and automatic detection of the surface (tracks, roads...). It functions on the basis of the highest accuracy in the coordinates on the cloud, and not as the arithmetic mean of the cloud heights. After the relative registration is done, the corrected point cloud (Figure 3) is saved as the first iteration.

In the second iteration, the absolute registration of the point cloud is done. It represents point cloud georeferencing, that is, entering the coordinates of control points recorded in the field. With absolute registration, the best accuracy of point cloud registration is achieved.

POINT CLOUD CLASSIFICATION

Point cloud classification is the process of organizing points into different groups based on certain characteristics. Classification algorithms can perform classification in different ways - based on height, point density, color, etc. (Lehtomäki et al., 2015). The needs of the projects determine the basis on which the classification will be made. Bentley MicroStation software and TerraScan extension were used for point cloud classification.

The first step in classification is automatic classification. Based on lines of code (so-called macros), the software distinguishes points by their height, density of points or some other criterion on the basis of which the classification is made. Macros are very useful when there is a large amount of data to classify, and the accuracy of the automatic classification depends on the precision of defining the criteria in the macro. After the automatic classification is completed, manual control is carried out.

Classification is a process that makes it much easier to spot objects of interest on a point cloud, and it is also possible to remove objects that cause a problem when detecting signs - for example, moving vehicles. It is very often used in robotics related to autonomous vehicles and general point cloud analysis (Lehtomäki et al., 2015).

TRAFFIC SIGN DETECTION

Traffic sign detection is performed on images captured by high-resolution cameras, which are part of the MLS. Each traffic sign has a pre-assigned code on the basis of which the detection is carried out. It can be manual or automatic.

Manual detection involves marking traffic signs on images by using a Bounding Box. It is a very long-lasting process, and for this reason today, the aim is to automate the detection, followed by manual control of the detection. In addition, manual detection creates a training set, that is, a set of data on the basis of which the neural network model for automatic detection of traffic signs will be trained.

Convolutional neural networks (CNNs) represent an extension of the multi-layer neural network model by adding a new type of layer, that is, a mathematical operation, to the equation representing the neural network. In this case, the input of the neural network is an image, which is represented as a pixel intensity matrix (Ševo, 2020). There are a number of models and ways of forming CNNs, but they are often impractical and slow. In order to speed up the detection process, the sizes of the regions (most often rectangles) that are used to search for objects in the images are often defined in advance. At the end of the process, the resulting rectangles are filtered and those that most accurately depict the objects of interest remain (Santos, 2017).

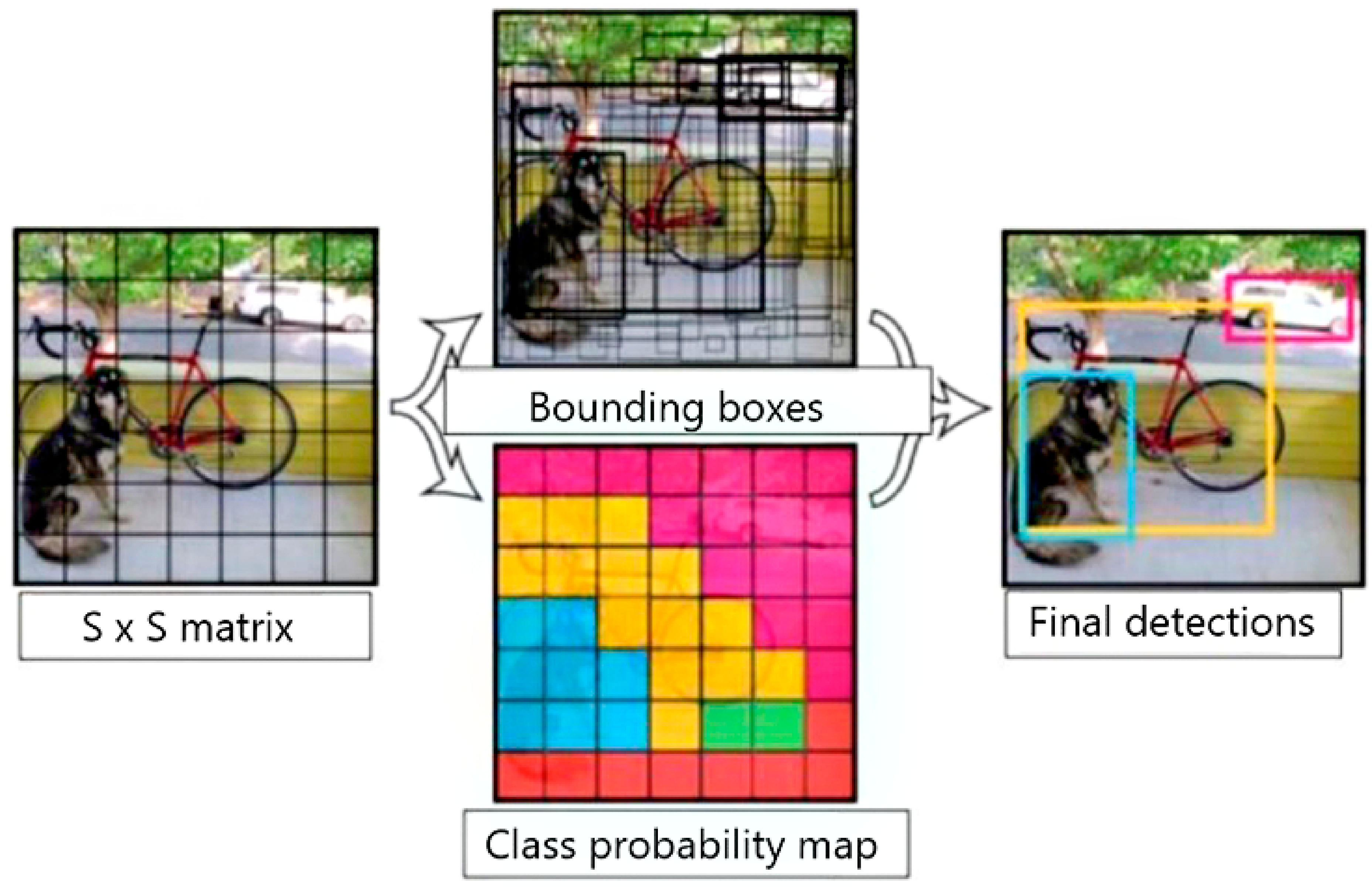

Figure 2. YOLO detection method
Source: Adapted from Ševo, 2020.

The YOLO method was used in the detection of traffic signs in this paper. The YOLO (You Only Look Once) detection method presented in Figure 2 generates regions of interest and excludes those that are not most accurately placed with respect to the class probability map. This method significantly speeds up the work of CNNs (Ševo, 2020).

It is often the case that one object is in several photos from different camera positions. Detected objects from one image get a 2D position in the local coordinate system of the camera. In order for the position to be correct, it is necessary to mark one object on at least two pictures. By using these data and the mathematical rules of triangulation, the position of the object in a certain coordinate system is obtained (Förstner, Wrobel, 2016).

Just as the point cloud is positioned in space based on the IMU/INS units and GNSS, so are the images. When scanning the terrain, the camera takes photos and each photo is assigned the time it was taken. Based on the recorded time, each image gets a certain position on the trajectory and can be connected to the cloud of points (Vasić et al., 2019b). The advantage of this procedure is that then the point cloud can be given information about the colors, which makes it much easier to analyze (Landa, Prochazka, 2014). The bounding boxes and central points of the detected signs in the photos can also be connected to the point cloud, based on the position in the photo, which significantly speeds up the process of extracting road infrastructure elements.

RESULTS

For the purposes of this scientific work, the results of the detection of traffic signs on 100 photographs taken in a city, in a length of 500 m, were analyzed. A total of 100 road infrastructure objects were detected in this area, of which 25 are traffic lights and street lamps, while the rest (75) are traffic signs. Advertisements and billboards are not detected.

All signs are marked with standardized codes from the catalog of German traffic signs (Verkehrszeichnen Katalog (VzKat)). Codes with values between 101 and 162 indicate warning signs, between 201 and 299 regulatory signs, between 301 and 590 informatory signs, and codes with values over 1000 indicate additional traffic signs. Signs with codes between 600 and 630 are temporary traffic signs. In some cases, there were signs for which no code was provided in the catalog, and additional codes were assigned to them, starting with the number 0 and followed by the shape of the sign (0_rectangle, 0_circle...). Three warning signs, 26 regulatory signs, 18 warning signs (of which five without a mark in the catalog), 6 additional signs (two of which without a mark in the catalog) and 22 temporary signs were detected in the investigated area.

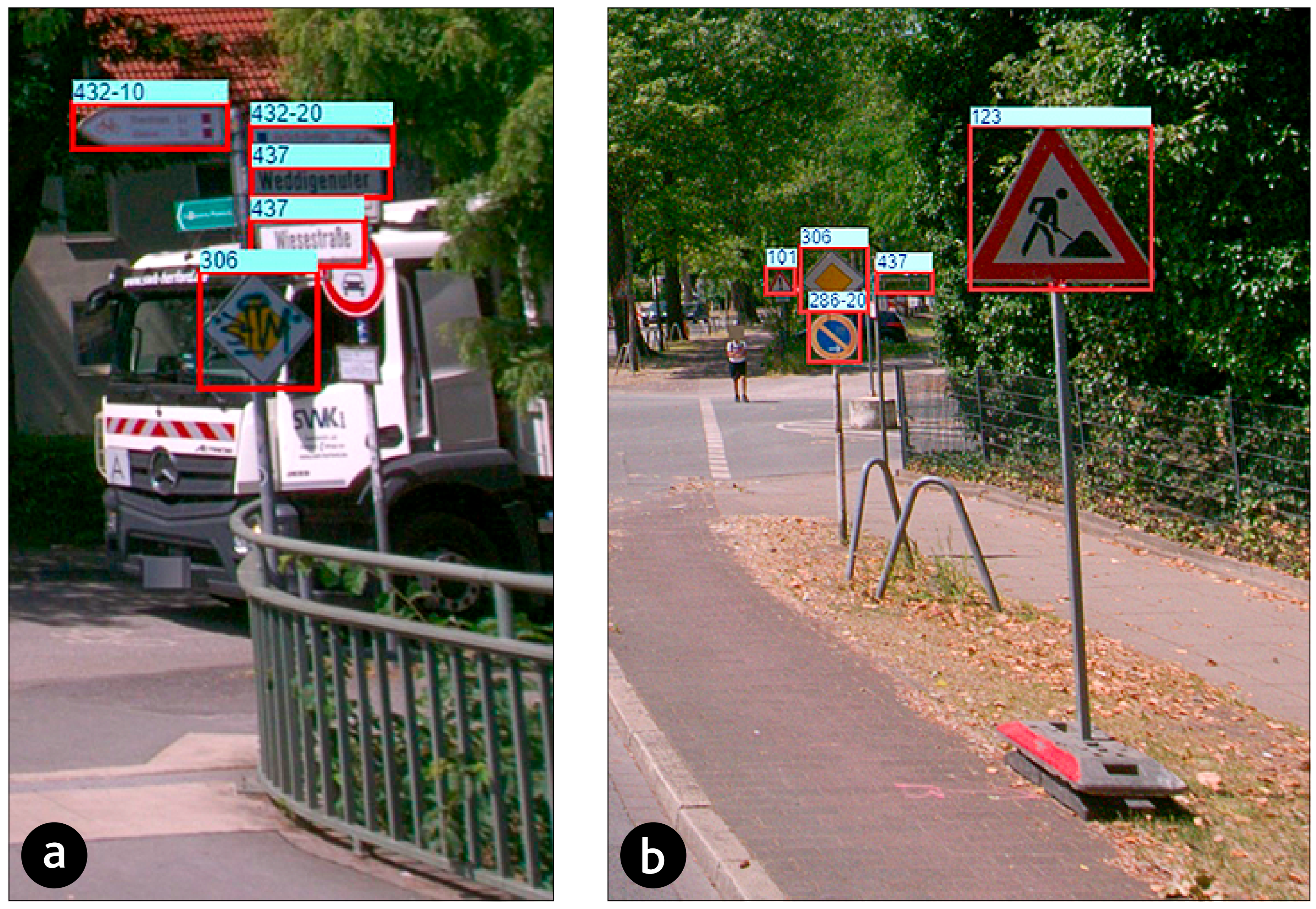

Figure 3. Detected traffic signs in the images

In the images above, there are snippets of photos with detected traffic signs. Five traffic signs were detected in both images, each of which was correctly detected. In the background of Figure 3a, three more traffic signs can be seen that were not detected, which is the result of the distance and insufficient visibility of these signs. After the detection, the photos are connected to the point cloud (Figure 4 a, b).

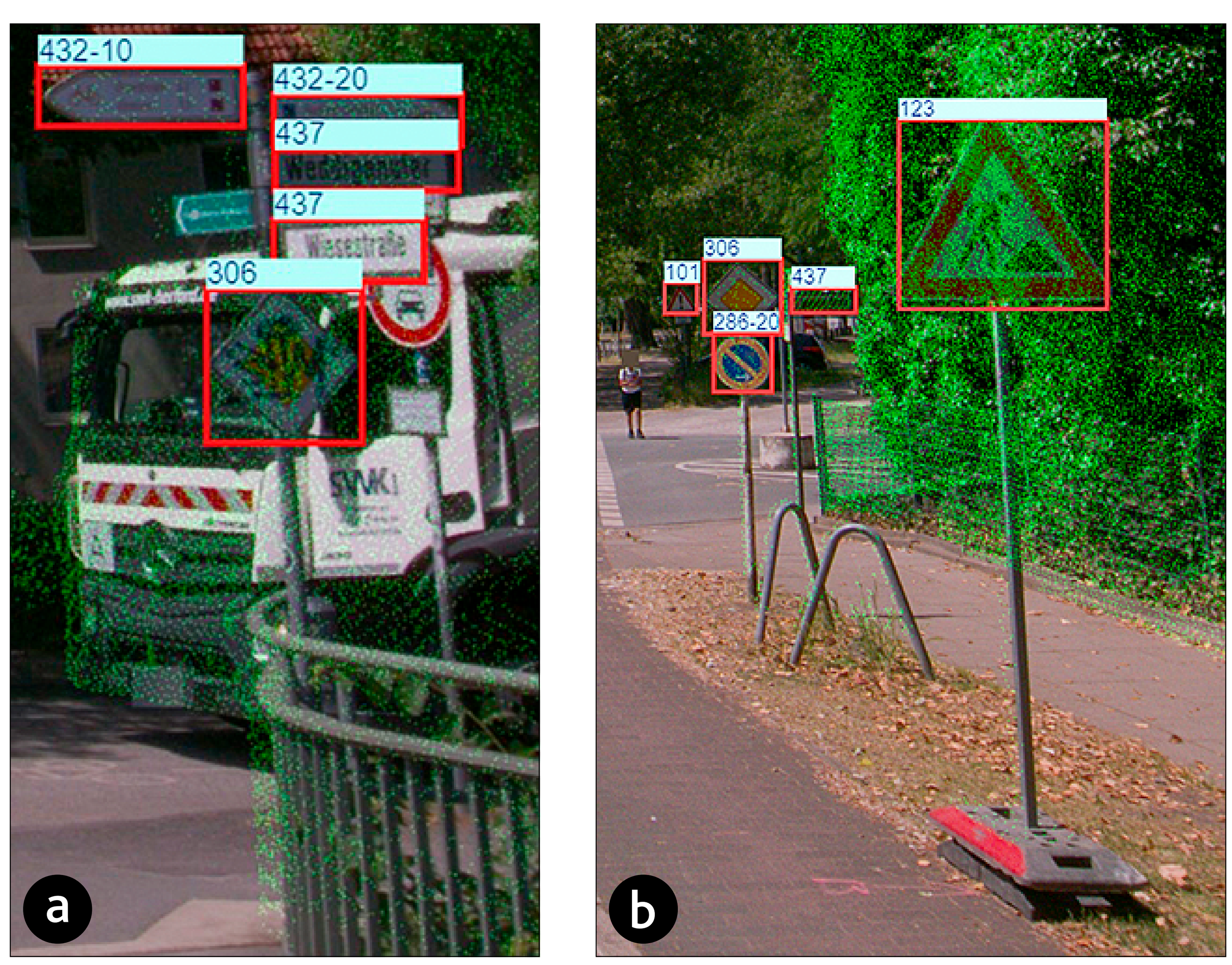

Figure 4. Images connected to the point cloud

In order to correctly connect the point cloud with the photos, it is necessary to carry out the previously mentioned processes - processing, registration and classification of the point cloud. The bounding boxes are given their place on the point cloud by this process and it is possible to extract them (in the form of a vector data type (*.shp)) so that they can be used in other software. The extraction of bounding boxes from photographs speeds up manual extraction and contributes to its accuracy. Figure 5 shows the bounding boxes (blue rectangles) and center points of the signs (red dots) on the point cloud opened in Bentley MicroStation software.

Figure 5. Display of the extracted bounding boxes of traffic signs

Vector data with locations of signs in the form of points can also be visualized in QGIS, where they will be placed at the exact location according to the appropriate projection, which in this case is ETRS89 / UTM zone 32N (EPSG:25832). Each point contains information about the sign code and location. Based on the code, each point is assigned a corresponding vector graphic symbol (*.svg format) and a map of all detected characters is made (Figure 6).

By visualizing the detected signs in QGIS, the process of detecting and then extracting traffic signs is completed.

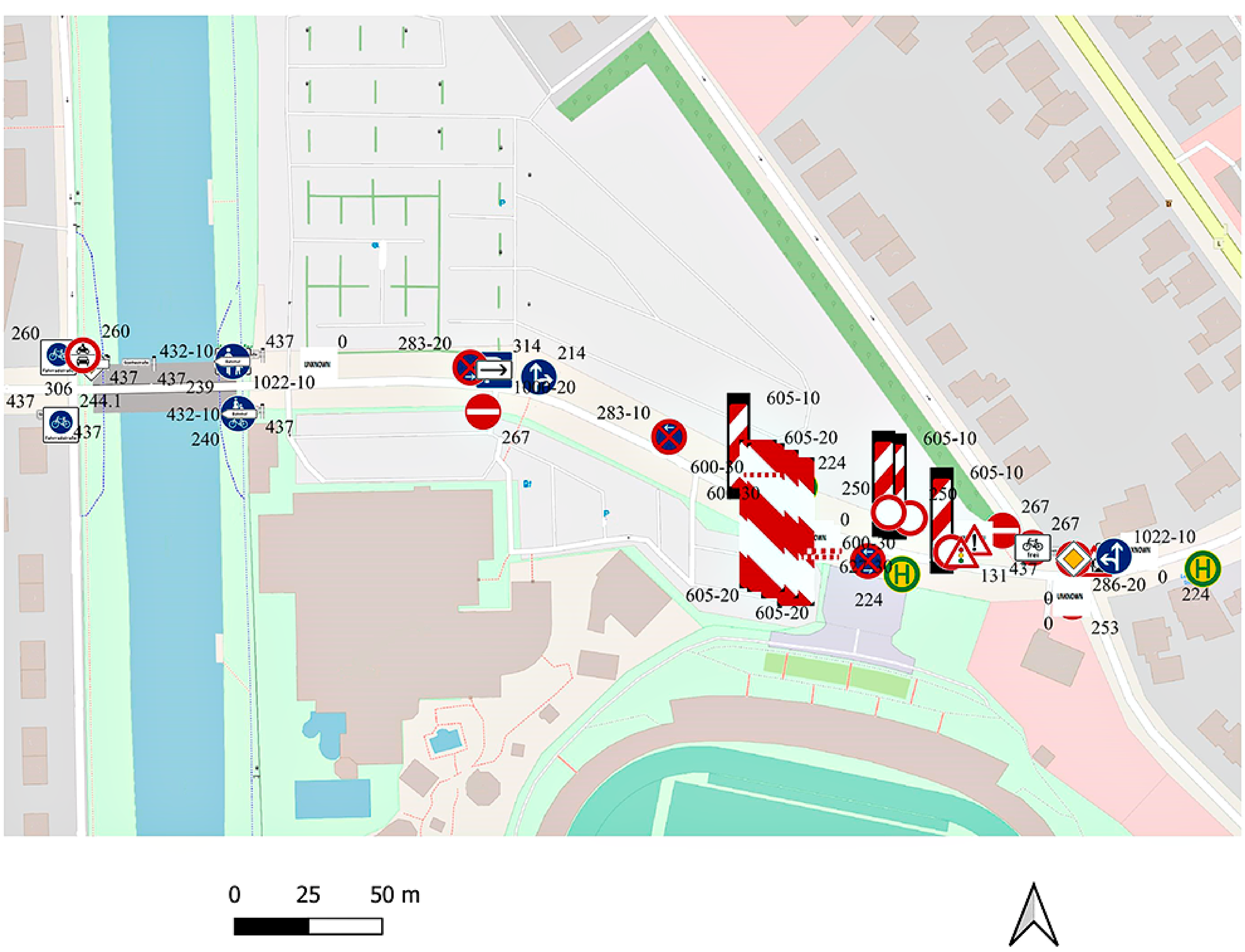

Figure 6. Map of the detected traffic signs

DISCUSSION

Based on the obtained data, a total of 75 traffic signs, numerous conclusions can be drawn. The overall detection accuracy is 83% (62/75). Most of the warning and regulatory signs (93%) were correctly detected. These are the signs that occur most often in traffic and are mostly simple in appearance, so it is not surprising that the accuracy of detection is very high. The informatory signs in this area were consisted mostly of street names and direction signs, which were very successfully detected. The percentage of successful detection of informatory signs (72%) was reduced by the relatively large number of signs that do not have their code in the catalog (Figure 7). These traffic signs had to be marked manually. A similar situation is observed in the scientific literature (Houben et al., 2013; Salti et al., 2015), where the accuracy of detection of informatory signs is 10% to 30% lower than the accuracy of the other two types of signs.

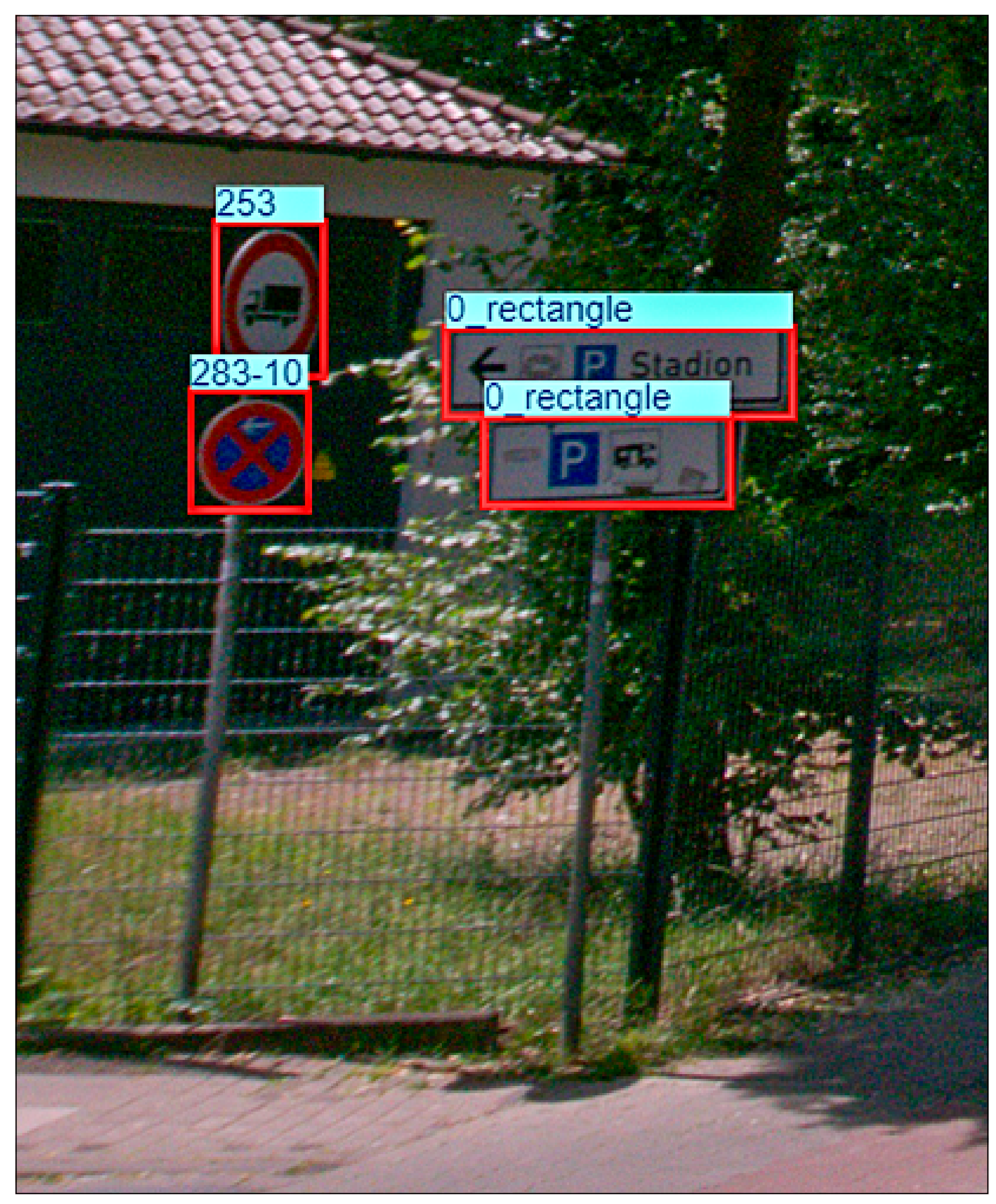

Figure 7. Example of the signs that do not have their code in the German traffic sign catalogue

On the other hand, additional signs were generally not recognized very well (67%). Namely, these signs are usually white with black letters, they have different content and each individual sign does not occur often enough for the software to have a large enough training set. Another factor is that the letters on these signs are quite small and until the vehicle is very close to the sign it is not possible to make out which sign it is. If a sign is poorly visible in each photo, it will not be marked for the purpose of training the detection software. Temporary signs were generally well detected (82%), and problems occurred with signs with opposite orientation of red and white lines. It is positive that there were no false detections, that is, all detected objects were traffic signs.

The distance of the traffic signs from the vehicle, i.e. the camera, certainly affects whether they are detected or not. More distant signs are smaller in the photos and it is harder to make out which sign it is. The signs are marked on a maximum of 10 photos, which represents a distance of 50 m from the vehicle. From this distance, very distinctive signs can be detected (like the rhombic right-of-way road sign - 306), signs with large images and symbols are detected mostly in 5-7 photos, and signs with a lot of text (most often informatory and additional signs) they were detected in a maximum of 3-4 photos. Therefore, the accuracy of detection increases with decreasing distance of the vehicle from the signs. This situation is also confirmed by the work of Belaroussi et al. (2010), where the detection accuracy on near signs is 20-30% higher than on distant signs.

In addition to these, many external factors also affect the detection of traffic signs. One of them are weather conditions. Weather conditions such as rain and fog can affect the quality of photographs and then detection is worse (Zhang et al., 2023). Furthermore, it happens that cars and trucks obscure some signs and they cannot be detected accurately. After the vehicles are removed from the point cloud by classification, it is possible to manually draw the bounding box of the sign, but the sign will certainly not be automatically detected in the photo. Some signs are oriented opposite to the orientation of the camera, so they cannot be detected only from the passage on one side. In all these cases, it is necessary to record the terrain several times, until all the necessary traffic signs are recorded.

The extraction of bounding boxes and central points on the point cloud is done with high accuracy (85%). Even after point cloud registration and classification, extraction problems may occur due to various factors. The most errors occur in areas where the signs are partially covered by vegetation, so the boundary frame can capture an unwanted part of the point cloud (Figure 8).

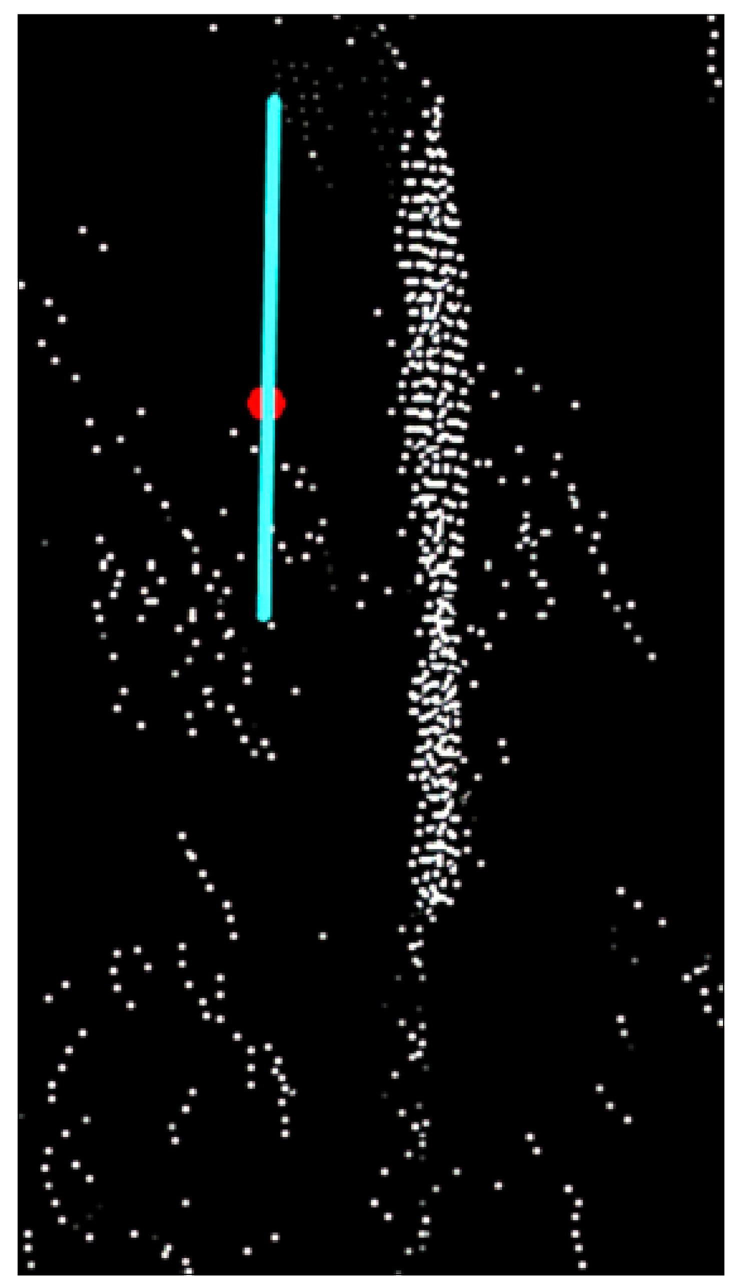

Figure 8. Example of the bounding box and central point marked on the vegetation behind the sign

Problems also arise because the traffic signs in the photos are not always visible at right angle to the camera. During detection, the angle of the bounding boxes cannot be completely matched with the angle at which the sign is located in the photo. Then, on the three-dimensional display, it can be seen that the boundary frame deviates significantly from the position of the traffic sign. In some cases, errors may occur due to non-matching or insufficient matching of point cloud with photographs. The solution in each of these cases is manual extraction of traffic signs directly on the point cloud. Some of these problems do not depend on the operators themselves, but on the data collection devices themselves, so these errors are much more difficult to fully eradicate.

CONCLUSION

The importance of collecting data on traffic signs is in the regulation and increase of traffic safety, and nowadays this process is very important for the development of computer vision and for the needs of autonomous vehicles. Manual data collection is a very time-consuming process, and modern geodetic technologies such as LiDAR (Light Detection and Ranging) and mobile terrestrial laser scanning (MLS) are increasingly being used. The collected data is processed in geoinformatics software, where the use of artificial intelligence is increasingly present to speed up numerous processes.

The data used in this paper were collected in Germany in 2022 using 3D laser scanning - LiDAR, more precisely MLS. Detection of traffic signs is performed automatically on photos using AI algorithms, namely YOLO detection method, in the form of bounding boxes.

On a total of 100 photos taken in the city, in a length of 500 m, 75 traffic signs were detected - three warning signs, 26 regulatory signs, 18 notification signs, 6 additional signs and 22 temporary signs. Each sign is assigned a corresponding code from the catalog of German traffic signs, after which the photos are connected to the point cloud. Then the extraction of bounding boxes and central points of signs was done. The visualization was done in two software - Bentley MicroStation and QGIS, when the detection process was completed.

By statistical processing of the results, it was established that the detection accuracy is 83% (62/75). The highest accuracy was achieved for warning and regulation signs (93%), and the lowest for additional traffic signs (67%). These results are related to the appearance of the signs themselves. The accuracy of detection is affected by many other factors, such as the distance of the signs from the camera and their size in the photo, weather conditions, the direction of movement of the vehicle, etc. The same problems appear in the scientific literature. The extraction of bounding boxes and central points on the point cloud was performed with a high degree of accuracy (85%), but there are also problems, such as signs covered by vegetation, mismatch of the point cloud and photos, and non-matching of the corners of the signs in the photo with the corner of the bounding box.

All the examples from practice confirm the conclusions of numerous scientific studies - the results are quite good, but there is always room for improvement. LiDAR and artificial intelligence are becoming the standard technology for collecting and then analyzing spatial data, in this case traffic signs. With the development of autonomous vehicles, this technology will be used every day, and the amount of the collected data will be growing. Through geoinformatics and geomatics, geography is becoming a very applicable science, which will aim at the daily monitoring and analysis of space, changes in space, but also making decisions about its improvement. This paper aims to contribute to the academic community by providing results from one concrete example from practice and presenting the current state of art, which is changing very quickly in today's conditions.

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