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AIRBORNE LASER SCANNER AS A DATA SOURCE FOR BUILDING SELECTED ELEMENTS OF AN INTELLIGENT DATABASE FOR TRANSPORTATION

Summary. In this study, the main objective was to detect the road network and key road infrastructure elements based on airborne laser scanning data. The study included identification of the road network and determination of its axes using three independent methods, as well as detection of horizontal signs such as pedestrian crossings. The analysis process was based mainly on digital image processing methods, based solely on lidar data, without using information from other sources. The results of the analysis showed that the use of lidar data provides a fast and effective method for continuously updating information on road infrastructure and expanding the transportation database. This potentially opens the door to effectively updating relevant data in the area of transportation infrastructure.
Keywords: airborne laser scanner, detection, image processing, transport

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1. INTRODUCTION

The road network is the main tool involved in individual and public transportation, both in cities and areas covered with scattered buildings, but also in intercity and international sections. Road transport is the most common form of movement, so it is important to have an up-to-date data set. Knowledge of the road network is vital information, used by a wide range of users, who have different ways of using the available data. They can serve, among other things, as a basis for the introduction of the Intelligent Transportation System (ITS) [1]. An intelligent transportation system is an advanced system based on information and communication technologies that aims to optimize transportation management and operations [2]. ITS uses various technologies, such as vehicle-to-vehicle (V2V) communication, vehicle-to-road infrastructure (V2I) communication, advanced traffic control systems, and data collection and analysis [3].

The goal of intelligent transportation systems is to improve the safety, traffic flow, efficiency and environmental performance of transportation systems. This includes applications in various modes of transportation, including roads, public transportation, airports, marine ports and other transportation areas [4].

For the smooth implementation of Intelligent Transportation Systems, their proper functioning and the sharing of results with the user, it is necessary to know the structure and elements of the road system in the area. Without this basic information, it is impossible to introduce further, more advanced information. Such data is collected and compiled in Poland by the General Directorate of National Roads and Highways.

Management of the national road network is an important issue, as it enables the proper operation and functioning of the nationwide transportation network. The road data bank built supports this task. It implements the issues and provisions of the decree of the Minister of Infrastructure in Poland [5]. According to these documents, the General Director of National Roads and Highways is required to collect data related to the network of public roads, bridges, tunnels, and ferries. The collected information is grouped in the form of databases, in which information on the state of the road network is available. Data describing the transportation network and characterizing the phenomena that occur within the road are collected in the Road Data Bank system. The detailed description of the components of the transportation network, coupled with statistical data pertaining to usage or traffic volume, enables one to observe the happenings, model the requirements of users, and effectively develop the transportation network to meet the expectations of the traveling public and meet the demands of society. And for the proper functioning and effective management of the road network, it is necessary to regularly update the database.

2. TRANSPORTATION NETWORK DATABASES

A transportation network database is a collection of structural information and data on the infrastructure, roads, routes, modes of transportation and other elements that constitute an area's transportation system. This database is used to analyse, plan, manage and optimize traffic and communications in a region. It stores vital information that enables the effective operation and development of the transportation system. Elements of the transportation network database may include, among others, road information, i.e., data on road types (highways, national roads, local roads), road numbering, length, width, number of lanes, location of road junctions, traffic circles, bridges and tunnels, information on traffic signs, traffic lights, pedestrian crossings, information signs and their location.

The transportation network database is a key tool for government institutions, local authorities, transportation companies and others involved in planning and managing traffic and transportation infrastructure. With proper analysis of this data, decisions can be made to improve the efficiency, safety, and sustainability of the transportation system. Developing infrastructure: investments in expanding and upgrading roads, highways, and public transportation systems can increase traffic capacity and fluidity.

Various methods and sources of information can be used to collect data for the construction of a road base. The most common method to collect data on the road network is field surveying. However, such a solution is very time-consuming and expensive, especially for extensive areas. With the development of technology, opportunities for faster data collection have emerged. One way to collect data can be through maps and geospatial information systems (GIS), such data information on road locations, road signs, pedestrian crossings [7]. Mobile and GPS technologies provide another method of spatial data collection and analysis. The use of mobile applications equipped with GPS technology enables the collection of information on location, travel routes and speed. Among researchers and professionals, there are some who focus on the basics of deep learning to better process and analyse the collected data [7]. Others, however, focus on applications that run on mobile devices and discuss a wide range of applications, from basic navigation to complex traffic analysis systems [8].

Another group of researchers focuses on the applications of these technologies in urban areas. They describe in detail how mobile applications and GPS sensors can be used to monitor and manage urban traffic, optimize public transport, and urban planning [9].

Other very frequently used data for the construction of a road infrastructure base is photogrammetric data, which, using photogrammetric methods, allows precise detection and analysis of the road network. Among these methods, two streams are noticeable.

The first current uses high-resolution aerial photographs. In this group, solutions based on image segmentation are introduced, which allow the identification of individual road infrastructure elements. Segmentation is often supported by techniques for tracing the road structure in the images and shape analysis, allowing a more accurate representation of the road network. The authors of [10] describe a method using vector field learning to extract roads from high-resolution images. In contrast, the paper [11] reviews various road extraction techniques, highlighting the importance of shape analysis and image segmentation. They also use morphological operators [12] and thresholding techniques [13] to extract road structures from satellite images, enabling accurate detection and analysis of shapes and road structures in images. On the other hand, the paper [14] introduced solutions for updating vector road maps from high-resolution images, using change detection at road intersections and directed road tracking. All of these approaches, whether based on high-resolution aerial images or using morphological operators and thresholding techniques, are key to the effective management of road infrastructure and the monitoring of changes in the landscape. They allow databases to be updated on an ongoing basis and decisions to be made regarding the development and maintenance of the road network based on the most up-to-date and precise information available through modern photogrammetric and remote sensing technologies.

A second approach to road network detection based on photogrammetric data is the use of airborne laser scanning data. LiDAR data allows precise mapping of terrain heights and objects on the ground surface, which is extremely useful for landscape change analysis and urban planning. These techniques also allow for point density analysis and the detection of anomalies in terrain structure, which can lead to the identification of new or altered roads and paths [15].

Both approaches, whether based on high-resolution aerial images or using laser scanning, are crucial for the effective management of road infrastructure and the monitoring of changes in the landscape. They allow databases to be updated on an ongoing basis and decisions to be made regarding the development and maintenance of the road network based on the most up-to-date and precise information available through modern photogrammetric and remote sensing technologies.

3. AIRBONE LASER SCANNER AS A DATA SOURCE

LiDAR is an active remote sensing system that first generates a laser pulse and then records the energy reflected from a given surface. Knowing the time the signal was generated and when it was received, as well as the properties of the generated light wave, it makes it possible to determine the distance to the object [16].

The obtained information is collected and stored as a spatial point cloud. Each point, in addition to three coordinates (X, Y, Z), can be assigned such information as reflection echo, reflection intensity, scanning angle, information on R, G, B components, as well as the layer to which the point belongs after classification. The classification process involves dividing the cloud points into a dozen layers. These layers are defined by ASPRS (American Society for Photogrammetry and Remote Sensing), the main ones being 2 – Ground, 3 – Low Vegetation, 4 – Medium Vegetation, 5 – High Vegetation, 6 – Building. The primary and compatible data exchange format is LAS. Additional information significantly expands the areas of data use [17]. A large part of point cloud-based road detection algorithms involve rasterizing the data using attributes, i.e. the height and slope of adjacent pixels [18], features of continuousness and homogeneity [19], and reflection intensity, based on which pixels are grouped [20].

The purpose of the present research was to test the effectiveness of methods using airborne laser scanning for the rapid detection and completion of selected road infrastructure elements, which are an important part of transportation databases. The research specifically focused on roadway centreline identification and pedestrian crossing extraction using data acquired from airborne laser scanning.

4. DATA AND DETECTION OF SELECTED ELEMENTS OF ROAD INFRASTRUCTURE

The research used a point cloud derived from airborne laser scanning, which was acquired as part of the ISOK project. The ISOK project is an IT system for country protection against extreme hazards, aimed at protecting the environment, economy, and society against disasters, mainly flooding. The ISOK project is co-financed by the European Regional Development Fund as a part of the Innovative Economy Operational Program – Priority Axis 7.

In the present project, the study was carried out for a fragment of the area of the city of Kraków. The analysis covers district II – Grzegorzki in the area of Starowislna, Dietla, Grzegorzecka, Pokoju Avenue, Podgorska, Kotlarska, Powstania Warszawskiego Avenue and Grzegorzeckie Roundabout, as well as part of district XIII – Podgorze, in the area of Kotlarski Bridge and a fragment of Gustaw Herling – Grudzinski Street. The area with an area of about 2.25 km^2 is mainly built up with compact buildings, with facilities for various types of services and office space, as well as residential areas. The Vistula River flows through the study area, and the Krakow-Tarnow railroad line is carried out.

The point cloud used in the study, is of a density of 12 points/m^2, with an average distance between points of about 0.3 m, is recorded in the PL-1992 plane rectangular coordinate system and the PL- RON86-NH altitude system. The data is classified according to ASPRS standards and saved in files in LAS format. Nine files described by symbols were used in the project: M-34-64-D-d-2-3-1-2, M-34-64-D-d-2-3-1-4, M-34-64-D-d-2-3-2-1, M-34-64-D-d-2-3-2-2, M-34-64-D-d-2-3-2-3, M-34-64-D-d-2-3-2-4, M-34-64-D-d-2-3-3-2, M-34-64-D-d-2-3-4-1, M-34-64-D-d-2-3-4-2 (Fig. 1).

Fig. 1. The study area on the background of the orthophoto with a split into the ranges of each file

4.1. Detection of road network

In order to build and develop the transportation network and ways of efficient management and management, there are automatic and semi-automatic methods of road detection. These methods are mainly based on the use of photogrammetric and laser data. In general, road network detection methods are based on the construction of point cloud rasters. The rasters can be built based on elevation, echo, or reflection intensity. In the next steps, the extraction of information on linear elements (roads) is possible through the use of digital image processing methods [21].

The first stage of the present study involved the extraction of the road network. For this purpose, the point cloud was classified into two layers: road and non-road. First, a raster with a mesh equal to 0.5m was constructed using single reflection intensity. A pseudo raster was created using inverse distance interpolation. The use of these types of points allows extracting from the entire set of points reflected from "hard" surfaces (road), which completely return the signal and do not allow registration of subsequent echoes. Wanting to perform classifications using reflection intensity, it is necessary to know the ranges of pixel brightness values for each class. For this purpose, a test field consisting of 115 pixels was made, which makes it possible to determine the limits. The points included in the samples represent the surface of wide and multi-lane main roads and local roads. A breakdown by type of pavement was not performed, due to the small variety of them in the study area and the difficulty of manually separating them. The distribution of the selected points along with the intensity image is shown in Figure 2.

Intensity values from the raster generated earlier were assigned to the indicated points. Based on these, limit values corresponding to roads were calculated.

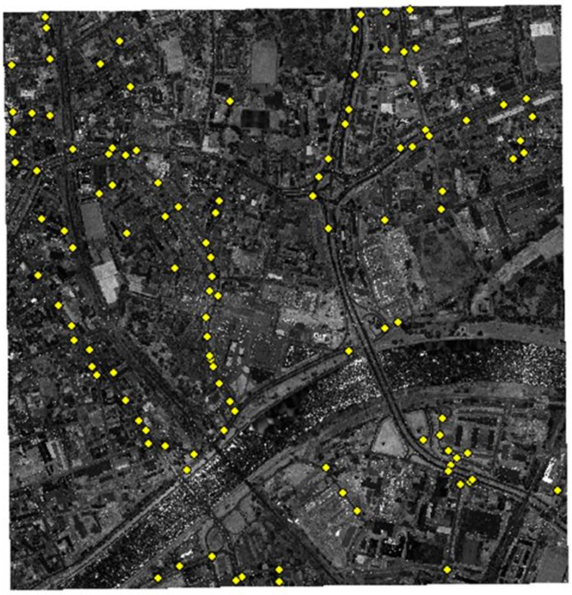


Fig. 2. Distribution of points representing roads on the intensity raster

The classification of points, which involves separating road areas, was done using the maximum likelihood method. In this method, one of the conditions is that the intensity values of the points representing the roadway assume a Gaussian normal distribution, which makes it possible to use the likelihood function described by the following formula (1):

$$L(X) = \frac{1}{(\sigma\sqrt{2\pi})} \exp(\frac{-(X-\mu)^2}{2\sigma^2}) \tag{1}$$

where:
X - intensity values assigned to a raster cell,
L(X) - the probability of X belonging to a specified class,
μ - the average intensity value for the tested sample of points,
σ - standard deviation.

In order to implement the above equation, the mean value of the points, standard deviation and threshold values were calculated. The maximum value of *L(X)* is taken when *X* is equal to the size of the sample mean, while the minimum threshold is reached for the smallest value of *X* from the test sample [21]. The calculated values are shown in Table 1, where the intensity raster was recalculated based on them (Fig. 3a).

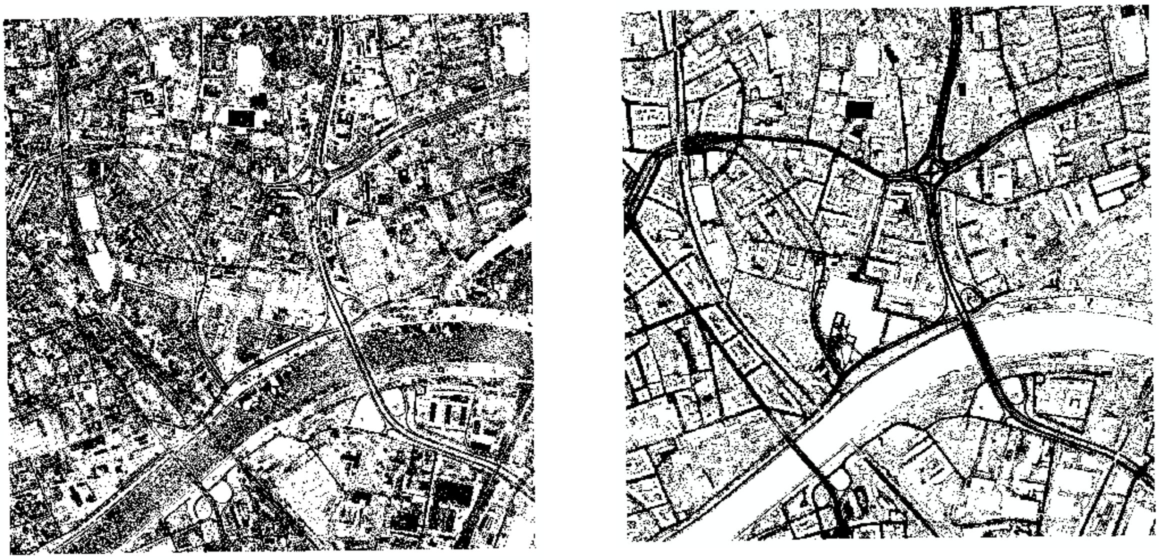
Analysing Figure 3a above, the outline of the road network is noticeable, but pixels representing other land cover elements have also been classified as roads. This has to do with signal reflection values, which can be similar for different types of surfaces. The use of intensity alone in the classification process is not sufficient to correctly detect the road network. Therefore, further processing was performed to narrow down the areas representing roads. First, pixels that represent land cover elements were eliminated. These elements are mainly areas located in the regions of buildings, where the intensity value of roofs was close to the limits of the selected intensity samples. For this purpose, a normalized Digital Surface Model (Digital

Surface Model – Digital Terrain Model) was generated from the points of the last reflection with a pixel size of 0.5 m. Using the nDSM, which contains height information, it is possible to eliminate those pixels whose value is greater than 0 (roads lie on the ground, so their height on the nDSM = 0m). The resulting raster is shown in Figure 7b. (Fig. 3b).

Tab. 1

Intensity values used in the road classification process

Parameter	**Value**
average (μ)	20,6
standard deviation (σ)	6,0
$L(X)$ min (for $X = 11$)	0,018
$L(X)$ max (for $X = 20,6$)	0,067



a) b)

Fig. 3. Binary images: black colour - detected areas (road network), white colour - surrounding areas a) obtained by performing the classification process, b) obtained by raster algebra using nDSM (normalized Digital Surface Model)

The obtained raster (Fig. 3b) clearly shows the road network. By introducing the height condition, it was possible to eliminate areas that represent the river, buildings and other elements that are not roads. These treatments significantly improved the detection of elements of the transportation network, but the image still has a lot of noise, single pixels that do not belong to the detected group. Furthermore, there are noticeable errors in the form of parking lots or other objects with flat surfaces, whose intensity is within the limits accepted for roads. Examples of errors are shown in the figure below (Fig. 4).

The next step was to use a median filter, which removed the noise in the image. Next, an opening operator was applied to the image. This transformation combines an erosion operation with a subsequent dilation based on the same structural element. The next transformation is a combination of functions related to the size of the objects, which is the extraction and subsequent removal of objects with a certain number of pixels. The raster was also subjected to transformations related to filling in "holes" in the road, created at pedestrian crossings or standing cars. A closure operator was used to fill "holes" occurring on detected linear elements [22]. All the processing of the digital image mentioned above significantly increased its readability (Fig. 5).

Fig. 4. Examples of incorrectly detected surface elements (playfields, parking)

Fig. 5. The resulting raster with the detected road network

To determine the exact course of the road network, the axes of the road network were detected. This process was performed by three independent methods. Two of them are related to the use of morphological transformations of the binary image, and the third solution is automatic vectorization.

The first morphological transformation is thinning, which reduces detected objects in the image until the element reaches a specific width, such as a single pixel. Filled objects are reduced to curves of a specific thickness, while when an object has gaps, a ring is created. The result obtained is shown in Figure 6a. It is noticeable that there are short sections that are not actually roadway axes.

The second method by which road axes were detected is skeletonization. This function is also designed to obtain a line of one pixel thickness from the elements in the image. In the process, a centreline with a preserved topology is extracted. In addition, there is an option to enter the minimum value of the segment, which allows removing from the image, short and at the same time incorrect fragments. The result is presented in Figure 6b.

The third solution tested is the process of automatic vectorization. This tool is mainly used to automatically determine the position of plot boundaries or contours from a scanned map. During automatic vectorization, a line smoothing parameter is defined. The results are vectors that have been rasterized so that a direct comparison with other methods is possible (Fig. 6c).

Fig. 6. The resulting raster with the detected road network – detection of road axes, by various methods: a) thinning, b) skeletonization, c) automatic vectorization

4.2. Extracting pedestrian crossings

Indicating the location of pedestrian crossings can be vital information for both pedestrians and drivers, but also for traffic managers. Such information may also be helpful in the context of special groups of pedestrians, which include children [23] or the disabled [24]. Collecting this type of data manually can be time-consuming. Therefore, an attempt was made to detect pedestrian crossings by a semi-automatic method using lidar data. The intensity of the reflections, as well as the RGB values that were assigned to the cloud points, were used to detect these elements. Horizontal signs, of their high importance in transportation and the need to make them highly visible in various conditions, are painted with reflective paint, which should also make them much easier to detect in rasters. The pixels representing pedestrian crossings painted on the asphalt stand out significantly from their surroundings, and the high contrast of the signs in relation to the pavement provides an opportunity to use such information in the processing of intensity images.

The first stage, of detecting pedestrian crossings, was performed analogously to road detection. The generated intensity image indicated 90 points, which were then assigned intensity values from the raster. From these, the mean value, standard deviation and limits were calculated according to formula 1. The range of intensities indicated for horizontal markings is too wide and includes pixels with different types of use. Therefore, an additional step that was introduced to improve the quality of detection is to act on the rasters obtained from the R, G and B channels. After generating the raster from the coloured points of the last reflection, the values from each channel at the test points were extracted. Based on the collected values, mean values, standard deviations and then limits were calculated, which were determined at distances of one standard deviation (σ) from the mean values. The calculated elements are summarized in Table 2.

Tab. 2

Values of parameters based on which pedestrian crossings were detected

Parameter	**Intensity value**	**Value - R channel**	**Value – G channel**	**Value - B channel**
Average (μ)	86,9	47156,5	46670,0	48853,5
Standard deviation (σ)	23,1	10229,0	9690,0	8509,3
L(X) min (for X = 42)	0,003	-	-	-
L(X) max (for X = 86,9)	0,017	-	-	-
Minimal	-	36927,5	36980,0	40344,2
Maximum	-	57385,5	56360,0	57362,8

After calculating the limit values, the common part was extracted from the areas determined in each channel (R, G, B) and from the image obtained after classification using the intensity parameter. The detected elements are not only pedestrian crossings, so a mask was applied in the form of a raster obtained in Section 4.1 presenting the detected road network. The result of the combined rasters is presented in Figure 7.

In this approach, in addition to the detected pedestrian crossings, additional elements painted on the roadway are extracted. In particular, the lines separating individual roadway lanes are well represented. To reduce the number of elements that do not represent the desired objects, image transformations were applied. Combinations of operations related to counting and removing groups of pixels of a certain number, morphological closure with a defined structural element, as well as basic operations, i.e. image difference, were used. When performing transformations, it was noted that the separation of pedestrian crossings from erroneous elements is not fully possible, despite the selection of various parameters. However, the achieved result makes it possible to easily perform the identification of the road horizontal marking elements in question (Figure 8).

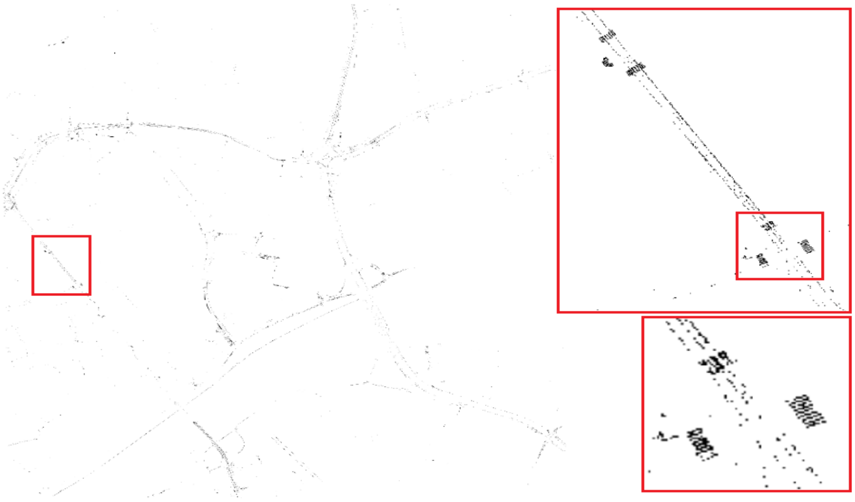


Fig. 7. The image resulting from the combination of the classification result and the mask formed from the detected roads – an enlarged fragment (elements detected are black)

Fig. 8. Resulting image of detected pedestrian crossings – enlarged section for the area marked in Figure 7 (Elements detected are black)

5. ANALYSIS AND ASSESSMENT OF THE ACHIEVED RESULTS

In order to practically implement new methods or use existing solutions for object detection, it is crucial to accurately estimate the precision and completeness of the detected elements. Therefore, this chapter provides a detailed evaluation of some of the results obtained.

5.1. Completeness of detection of specific elements

The completeness of the detected elements of the road network is crucial in evaluating the results. Too much generalization is associated with a reduction in the set of detected elements, at the same time, the “uncleared” data has too much incorrect information. Therefore, it is necessary to optimize the methods used accordingly. Detection of a road network from airborne laser scanning data using only intensity information does not give satisfactory results. Therefore, additional attributes, i.e. height and RGB, were used for the study. The analyses showed that the completeness of road detection is largely related to the width of the street. For wide and multi-lane traffic lines, the proposed algorithm performs better, as the object is mapped by a larger number of pixels. Small streets running through residential neighbourhoods or access roads were not included in the detected network in several cases. In addition, within residential roads, where cars park on the side of the road, the width of the road is incorrectly determined. The discontinuity of the band of the detected road also appeared in places where the road runs under a bridge or overpass. On the resulting raster, there are also areas assigned to roads that are not actually roads. These are elements that have similarity in intensity, but are often large flat areas that can be eliminated by applying appropriate image transformations and filtering, e.g. using shape, surface. The transport network has been largely correctly extracted. Figure 9 shows where there are deficiencies of only narrow streets in residential areas. In contrast, Figure 10 draws in sections of undetected streets. These sections account for about 21% of all streets located in the area. A portion of the undetected roads are not covered with asphalt pavement, which was included in the analyses.

Another aspect of the performance evaluation is to check the completeness of detection of pedestrian crossings. Some of them may have been filtered out due to insufficient size or number of recorded lines, which may have been caused by cars left within the sign limits or problems in their detection related to physical wear and tear of the sign painted on the pavement. The number of detected crossings is also influenced by the shape and detail of the road network defined at an earlier stage, which acts as a mask limiting the areas of the extracted elements. Where roads have gaps, the error carries over to subsequent passages. The resulting map derived from the horizontal sign detection stage includes elements of other signs, such as fragments of lines separating adjacent roadway lanes. Therefore, only whether crosswalks were missed was considered in assessing completeness and correctness. Undetected pedestrian crossings are marked in Figure 9. Identification and inspection were performed manually using an up-to-date orthophoto. The automatic detection of pedestrian crossings is satisfactory, as in an area of more than 2 km^2, only a dozen is missing. About 75% of the horizontal signs (pedestrian crosses) present were correctly detected.

5.2. Accuracy of road axis detection

The completeness of the detected data is the basis for evaluating the accuracy of road axis detection. In this study, three different methods were used to generate axes. The purpose of this subsection is to determine how accurately the axes are represented and which of the methods used is the most advantageous.

A visual analysis was performed first. The image generated by the automatic vectorization process has the smoothest lines, but the joints of individual edges, e.g. intended to represent an intersection, are not smoothed and do not transition smoothly from one to another. Thus, the image does not reflect the actual shape of the axis and looks unnatural. The use of a smoothing filter gives more satisfactory results visually. The edges of the streets are clear, and the corners and intersection areas smoothly reproduce the transition between lines. The downside of the image derived from the discussed function is the occurrence of "branches." These are small lines, misrepresenting the axis of the road, but significantly disrupting the visual perception and evaluation of the method. Similar anomalies are formed using skeletonization, but in this case, already at the stage of determining its parameters, it is possible to eliminate such sections when adopting a length criterion for them.

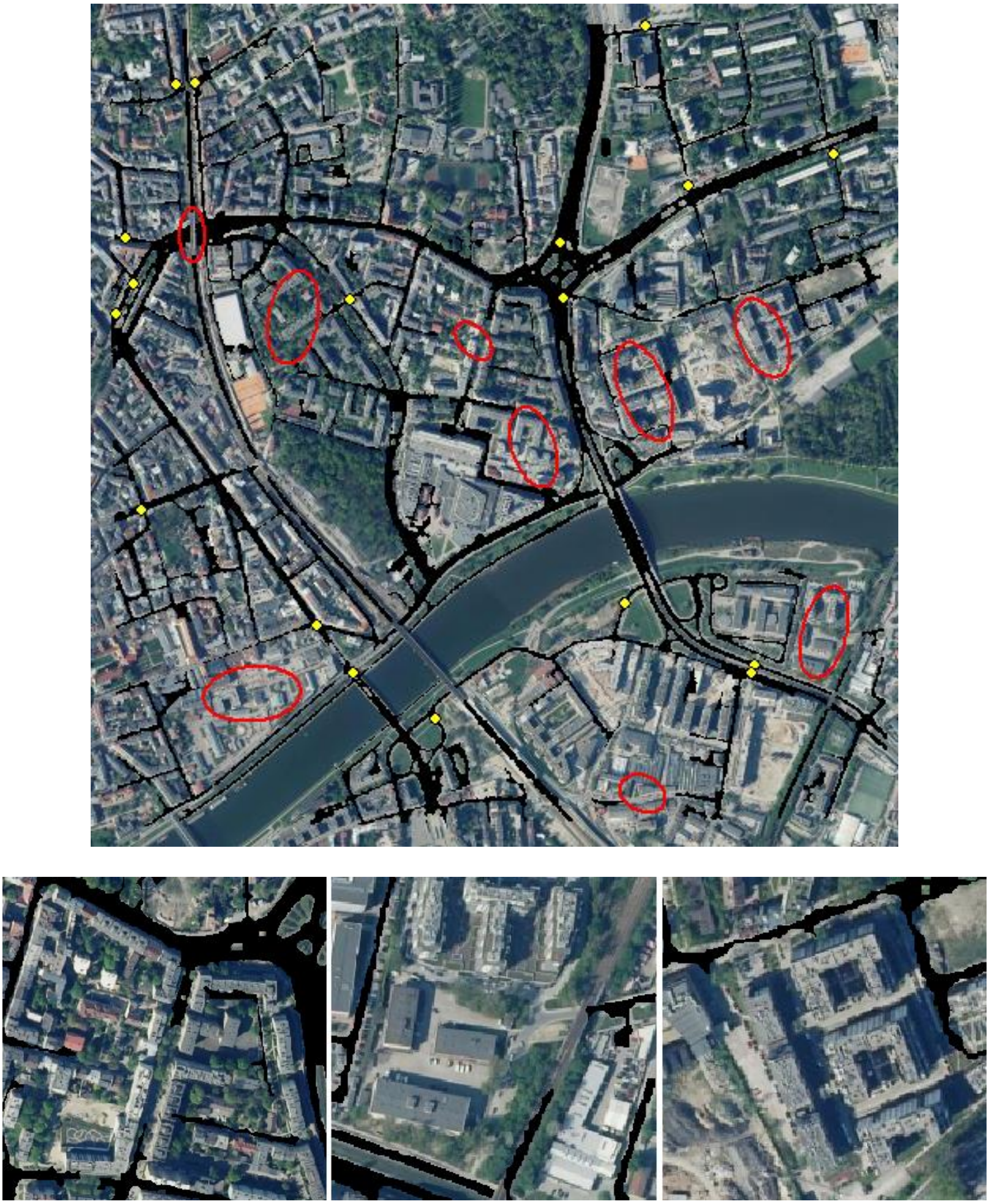


Fig. 9. Final rasters overlaid on the orthophoto with examples of areas where the road was not detected (red, enlarged sections) and pedestrian crossings that were not detected (yellow dots)

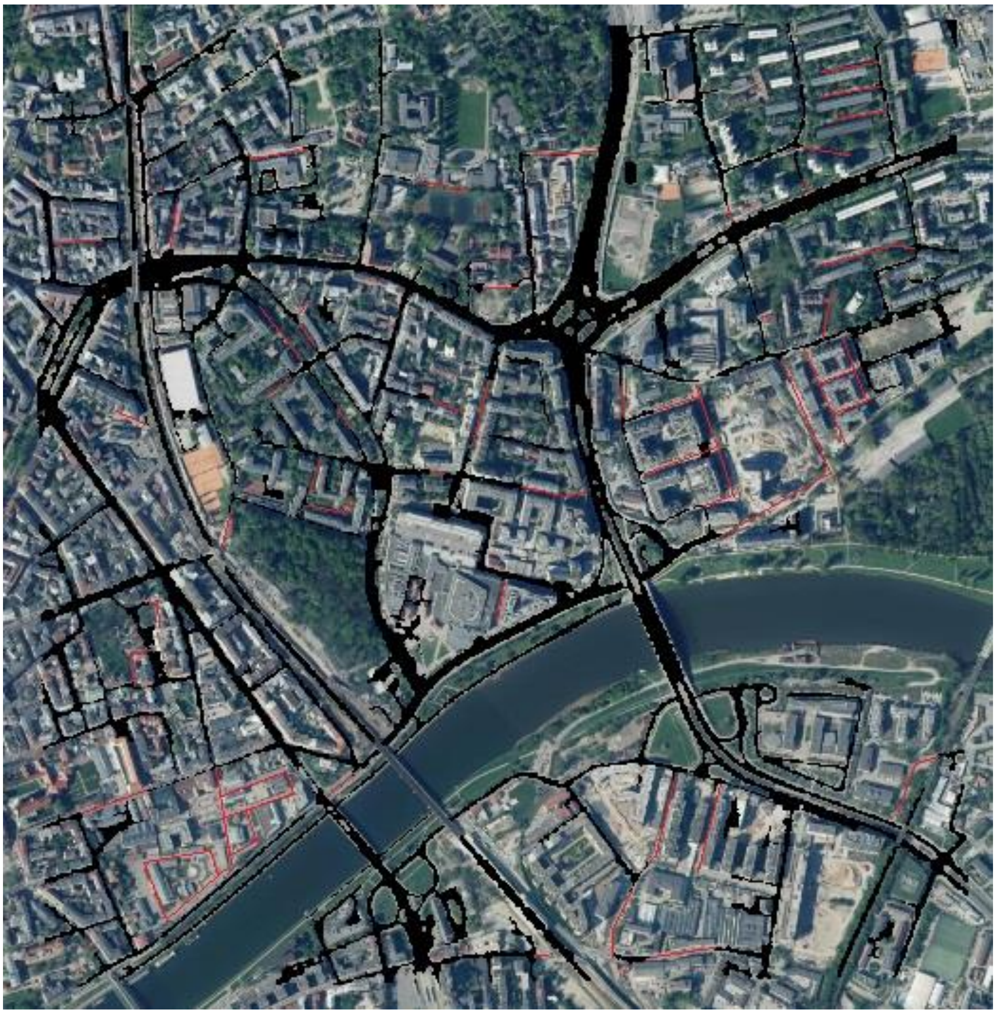


Fig. 10. Detected roads and drawn in segments representing missing roads (red)

Such a solution combined with the shape of the line similar to that created from the application of the smoothing filter gives a certain advantage. From this, it can be judged that, performing the evaluation from a visual point of view, the most favourable results were achieved using the skeletonization method. When performing visual analysis of the detected axes, attention should be paid to the traffic circle, which is located within the area. It is a heavy element to extract axes due to its shape. An additional complication is the streetcar tracks running through the centre and crossing each other, which were also detected. Axis detection in this area was not performed correctly. Each of the tested algorithms showed problems with drawing the axes in this area, failing to define which elements should be connected to each other. The results produced using the subsequent functions are shown in Figure 11, but they could have been used for subsequent analyses, some refinements and transformations in the methods would have to be made, other tools would have to be sought, or the problematic section would have to be worked out manually.

To check the accuracy of road axis detection, reference data was used. A road network manually vectorized from an orthophoto was used as reference data. A database of 82 points located on road axes was constructed. These points served as reference points. The points were distributed on both main and side roads, on straight sections and on curves. In the next step, the distances from each identified reference point to the detected road axis were determined for each method separately. Based on the collected length values, the average values for each method and their mean-square errors were calculated (Tab. 3).

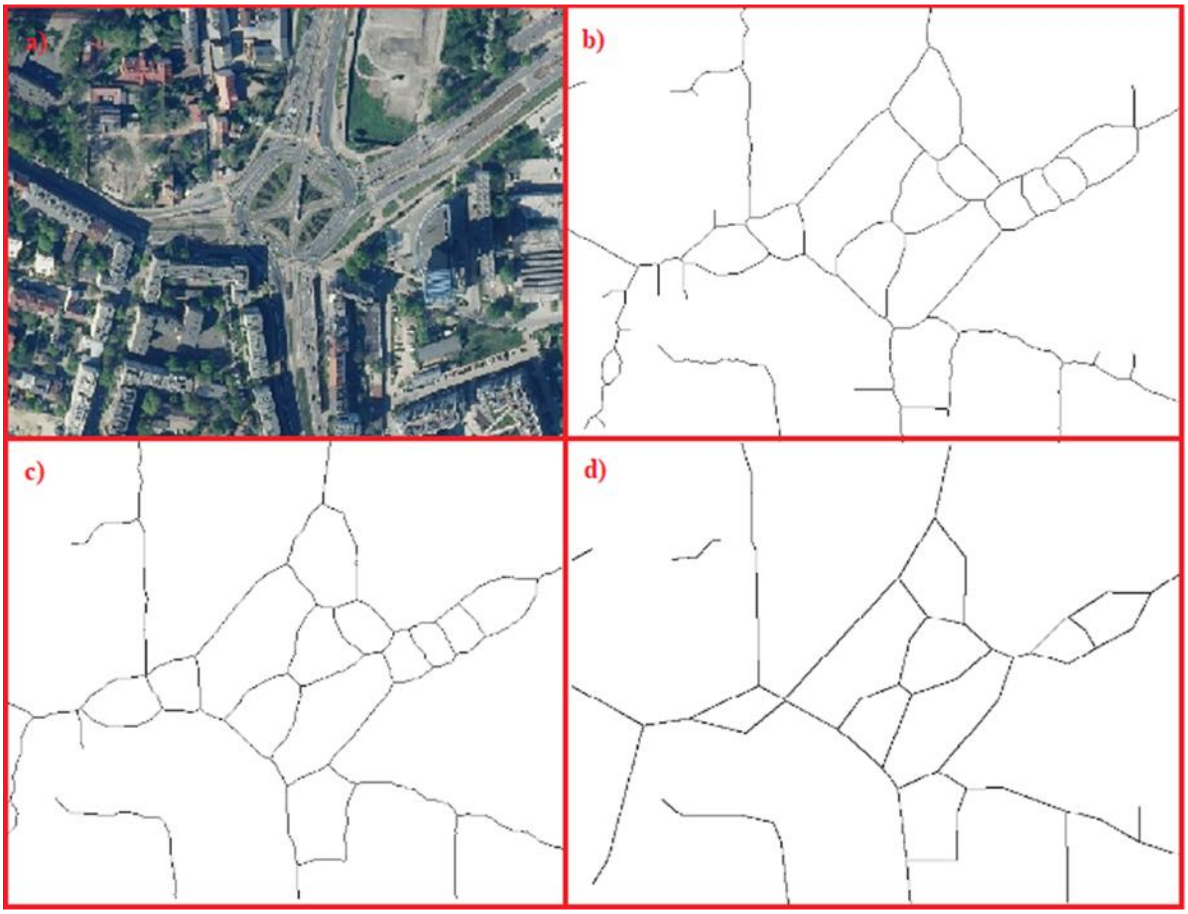


Fig. 11. Drawn axes road in the traffic circle area: orthophotos (a), application of smoothing (b), skeletonization (c), automatic vectorization (d)

Tab. 3

Summary of the calculated distance values for the various methods of extracting the road axes

Methods:	**Thinning**		**Skeletonization**		**Automatic vectorization**	
	82 points	**71 points**	**82 points**	**71 points**	**82 points**	**71 points**
Average reference point-axis distance [m]	1,75	0,86	1,84	0,92	2,42	1,43
MSE [m^2]	7,52	1,17	8,33	1,38	12,48	4,79
RMSE [m]	2,74	1,08	2,89	1,17	3,53	2,19

Analysing the results obtained from the conducted tests, it is noticeable that the average distance between the reference points and the generated axis achieves the best results when using the thinning technique. This method was favourably evaluated, considering the visual aspects and the shape of the detected axes. However, its significant limitation is the generation of "branches" that limit correct identification and introduce erroneous elements. Such an imperfection is not present in the result using the skeletonization method, which positively influences the final perception of this method despite obtaining weaker RMSE values. The lowest accuracy was obtained in the automatic vectorization method. It is worth noting that all 82 points were used for the initial analysis. It was noted that for some distances significantly differ in the three methods studied. Particularly, this situation was observed in the case of streets consisting of two carriageways, where there is a green belt or a tramway track between them. After digital image processing operations, the area between the carriageways was also identified as a road, resulting in the generation of a single axis running through the centre of the dividing lane, with the reference point placed in the centre of one of the carriageways. Similar situations occurred when there was a bicycle path or plaza in close proximity to the edge of the road. These objects were partially identified as part of the road, resulting in a shift of the generated road axis and significant differences in position. Another case that distorts the results is a traffic circle located within the study area. In the case of this element, the analysis for the algorithms became difficult because streetcar tracks crossed in the middle of the traffic circle, which proved to be unmovable. These elements introduced additional disturbances, which caused the functions used for axis extraction to not work properly. In order to eliminate the impact of such cases on the accuracy assessment, in the example studied some points were excluded from the analysis, leaving 71 points. As a result, two columns of points are summarized in Table 3 for comparison.

6. CONCLUSION

The aim of this study was to detect selected elements of the road infrastructure using, exclusively, airborne laser scanning data. The first element focused on was the shape of the road network. This was based on the point intensity attribute, and detection was performed on the generated rasters. One of the key issues in image classification is identifying the right number and location of points with the right intensity. In the area analysed, most of the road surface was asphalt, but despite the same material, the range of reflection intensities was quite wide. The intensity is influenced not only by the type and colour of the pavement, but also by the angle of incidence of the pulse. So the input set of points with a certain intensity is wide, resulting in the detection of a much larger number of objects on the ground surface. But using appropriate digital image processing, redundant elements can be automatically eliminated. However, the algorithms used did not cope very well with the automatic detection of roundabouts. In this case, manual correction is necessary. Narrow roads can also be problematic, especially on housing estates, where their detection is also adversely affected by shadow. Despite a few undetected elements, the final results can be described as satisfactory. The main roads were detected correctly, and it must be borne in mind that only lidar data was used.

The detection of pedestrian crossings is the next stage of the study. This stage was based on indicating test points and then calculating boundary quantities from the intensity parameter values. Identifying the points proved to be a relatively difficult task so that they represented the entire intensity range for all crossings. Horizontal signs painted with specialized paint have a characteristic level of pulse reflection, but not all stripes are renewed frequently enough.

The worn-out paint looks slightly different on the intensity raster, and the range that needs to be extracted increases significantly, making the task of subsequent filtering more difficult. Even despite the integration of the classification results from the intensity image and the individual RGB channels, as well as the overlay of a mask related to the road network, many elements were incorrectly indicated. The mask itself, created in the previous project stage, can result in transitions located on roads not previously detected being removed from the image. A large proportion of the redundant areas included other horizontal signs painted on the street surface, i.e. lines separating individual carriageway lanes. The difficulty in image processing is to use filters that allow pedestrian crossings to remain while removing unnecessary objects. It is a very time-consuming process to choose the right function parameters to get the desired result. However, despite these difficulties, the end result was satisfactory and the extracted data (pedestrian crossings) can be used to complete the database.

LiDAR provides a broad set of data which, once the appropriate attributes have been selected and transformed to suit the type of object, offers the possibility to gather such information, which both on its own and in combination with others collected in the database, can provide unique knowledge that is crucial in the intelligent management of the road network, as well as the entire city. Observing the appearance of the developed point cloud derived from airborne laser scanning, it should be noted that its density may not be sufficient to detect point features such as vertical road signs or traffic lights. Such objects are too small, to LiDAR ensure respectively large coverage of their points, which would give the chance to their distinction. However, the accumulation of such data may be possible after the integration of e.g. with the scanning of the terrestrial or mobile scanning, or lidar acquired from UAV. The lidar data offers a range of possibilities for the detection of road infrastructure elements, which can significantly facilitate activities related to the creation and expansion of the database used for transport.

Comparing the results of the research carried out with the latest developments in the detection of road infrastructure using LiDAR, several important aspects can be noted. Nowadays, methods using deep neural networks [25] and hybrid techniques [26], which improve the precision of detection and automation, reducing the need for manual correction, are increasingly being applied. These new approaches have the advantage of being better able to deal with pavement heterogeneity and shading, which was problematic in this study. In addition, the latest technologies using high-resolution remote sensing images for detection improve classification accuracy, enabling better differentiation of pavement materials [27]. Contemporary research indicates that the use of advanced machine learning and artificial intelligence algorithms can significantly speed up the data analysis process, while eliminating many of the errors associated with manual interpretation. Nevertheless, some challenges, such as the detection of complex structures (e.g. roundabouts) and narrow roads, still require further algorithm improvements. Detection of point infrastructure elements such as road signs also remains problematic, which can be improved by integrating data with terrestrial or mobile laser scanning. Additionally, data from sources such as drones [28] can provide more detailed information that is difficult to obtain with traditional airborne laser scanning. Overall, the latest technologies offer promising solutions that can significantly increase the efficiency and accuracy of future research in this area. The integration of different scanning techniques and advanced data processing could be the key to fully automating and the optimization of road infrastructure management processes.

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The data presented in this study: (.las files) are available in ISOK project – available at: https://isok.gov.pl/index.html and also ortophotos are available on National Geoportal Available – https://www.geoportal.gov.pl.

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