Automated Extraction of Road Median from Airborne Laser Scanning Data

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KEYWORDS: Airborne Laser Scanning, Attributes, Road Median, Frequency Distribution, Knowledge Analysis.

ABSTRACT

Airborne Laser Scanning (ALS) systems enable the acquisition of an accurately georeferenced set of 3D dense point cloud data that can be used to develop more efficient approaches for managing road infrastructures. These systems can contribute to the production of useful knowledge about road median, which is a narrow strip of land that separates traffic on opposite sides of the road. The road median is one of the fundamental feature, whose correct identification is a prerequisite to obtain precise information about road and other objects along it. The acquired ALS data can be used to locate, measure and classify the road median in a timely and cost-effective manner in order to facilitate their maintenance. In this paper, we present an automated algorithm for extracting road median from ALS data. We use the road vector polylines to reduce the search space in the LiDAR data, which enables a more accurate estimation of the road median. The frequency distribution of elevation values is used to remove the crossing highways above the road sections. We threshold the LiDAR elevation and intensity attributes to get an initial estimation of the road median. We make the morphological operations based knowledge analysis to complete the shape of road median and remove other road surface elements that are introduced through the use of thresholding. We tested our algorithm on two 1-km road sections consisting of distinct types of road medians based on concrete and grass-hedge barrier. The successful extraction of medians along these two road sections demonstrate the robustness of our automated algorithm. These research findings provide valuable insight and prototype road median extraction tool-set for both national road authorities and survey companies.

1. INTRODUCTION

Light Detection And Ranging (LiDAR) enables 3D surveying of real world environments by measuring the time of return of emitted light pulses. Laser scanning systems make use of this technology to acquire accurately georeferenced sets of dense 3D LiDAR point cloud data. They provide several benefits over conventional sources of data acquisition in terms of accuracy, resolution, attributes and automation (Mallet and Bretar, 2009; Lohani, 2016). Other benefits are high level of automation involved in data acquisition process and ability to acquire data beneath tree's canopy. Laser scanning systems provide an accurate 3D information about the location of terrestrial objects along with their geometrical and structural properties, which can be used to support a wide range of services and evidence based decision making. The acquired geospatial information facilitates the development of more efficient approaches for managing urban infrastructures and natural resources (Darnel, 2012). The information obtained through laser scanning systems have applications in road safety, urban planning, flood plain, glacier and avalanche mapping, bathymetry, geomorphology, bridge and transmission line detection, forest survey and many others (Burtch, 2002).

Airborne Laser Scanning (ALS) systems present a reliable tool for capturing 3D spatially referenced information about road and its environment. The applicability of ALS systems continue to prove their worth in road mapping due to the rapid, continuous and cost effective 3D data acquisition capability (Barber et al., 2008). They enable the acquisition of data that provides a number of attributes including elevation, intensity, pulse width, range and multiple echo, all of which can be used for extracting information about road and its features. The ALS systems can facilitate reliable and accurate acquisition of 3D spatially referenced data about road median, which is a narrow strip of land that separates traffic on opposite sides of the road. Accurate knowledge of road median also increases the reliability and precision of extracting other objects along the route corridor environment. The acquired 3D LiDAR data can be used to record, locate, measure and classify the road median in a timely and cost-effective manner in order to schedule their maintenance. This information can assist road authorities in effective management of the road networks and in ensuring maximum safety condition for road users.

The methods developed for extracting road features are mostly based on identification of planar or smooth surfaces and the classification of point cloud data on the basis of its attributes (Vosselman and Liang, 2009). Several methods have been developed over past decades for extracting road and its features from ALS data. Clode et al. (2004)

segmented ALS point cloud into road and non-road objects using a hierarchical classification technique based on elevation and intensity information. However, the accuracy of their road segmentation approach was reduced due to the presence of car parks and private roads in their survey area. Akel et al. (2005) identified roads from ALS data which were then used for generalising the Digital Terrain Model (DTM). LiDAR data was segmented by applying a region growing approach on the basis of surface normal direction and height difference properties and then the extracted segments were classified into road and non-road objects based on a certain set of decision rules. Elberink and Vosselman (2009) developed an automated method for 3D modelling of highway infrastructure using ALS data and 2D topographic map. The road polygons were extracted from the topographic map data using a map based seed growing algorithm combined with a Hough transformation. The LiDAR points were added to the corresponding road polygons using a LiDAR based seed growing algorithm. Subsequently, 3D reconstruction was achieved by assigning the third dimension to the map polygons. Samadzadegan et al. (2009) used a multiple classifier system to classify the ALS point cloud into road and non-road objects using first pulse, last pulse, range and intensity attributes. Different combinations of LiDAR attribute layers were classified based on different features using maximum likelihood and minimum distance methods. However, the optimum selection of features, type of classification technique and classifier fusion method were not conclusively addressed. Li et al. (2015) detected roads from ALS data by first applying filtering technique to distinguish ground and non-ground points. Histogram distribution of intensity attribute was used to segment candidate points and finally road points were detected based on roughness and area criteria. Hui et al. (2016) proposed a method to extract main road centrelines from ALS data. In their method, an optimal intensity threshold was estimated using the skewness balancing algorithm; narrow roads were removed using the rotating neighbourhood algorithm; while the influence of attached areas was avoided using the hierarchical fusion and optimization algorithm. He et al. (2017) analysed the capability of ALS data in updating highway asset inventory. In their work, ArcGIS-based workflow was developed to extract highway assets that included traffic signs, light pole, billboard, barrier, bridge and culvert. Various other methods have been developed for extracting road edges (McElhinney et al., 2010; Kumar et al., 2013, 2017; Serna and Marcotegui, 2013), road markings (Kumar et al., 2014; Guo et al., 2015), road surface roughness (Kumar et al., 2015; Diaz-Vilarino et al., 2016) and road poles (Teo and Chiu, 2015; Yan et al., 2016) from Mobile Laser Scanning (MLS) data. The point density of LiDAR data significantly impacts any feature extraction process in terms of computational cost and quality of extracted feature (Cahalane et al. 2014, 2015, 2016). The data acquired from ALS and MLS platforms differ in terms of accuracy, density and uniformity, primarily due to the distance of the scanner to the mapping objects (Rutzinger et al., 2009). Some attempts have also been made to integrate these two sources of datasets for extracting road and its edges. Boyko and Funkhouser (2011) presented active contour based method for extracting urban roads from a large-scale ALS and MLS datasets. An initial approximation of the road network in the point cloud was made using 2-D map, while the elevation based attractor function was used as an external energy of the active contours to find the road edges. Zhou and Vosselman (2012) presented a three-step approach for mapping kerbs from ALS and MLS datasets. First, small-height jumps were detected near the terrain surface; then, a sigmoidal function was fitted to mid points of the height jump, and finally, small gaps between nearby and collinear line segments were closed.

The ALS data is a rich source of 3D georeferenced information, whose volume and scale have inhibited the development of automated algorithms. The large volume of data produced by laser scanning systems lead to time consuming and computational expensive processes for automated features extraction. The majority of developed approaches attempt to detect road objects by distinguishing them from ground or non-road objects but do not focus on their precise and automated extraction. Most of these methods fail to provide an efficient and robust solution for extracting road objects. Little or no research has been reported to extract road median, which constitutes as one of the most fundamental feature along the route corridor environment. The elevation and intensity attributes from LiDAR data can be a useful source of information for extracting road median, which are required to be thoroughly explored. In this paper, we present an automated algorithm for extracting road medians from ALS data. The developed approach is based on frequency distribution, threshold and morphological operations based knowledge analysis of LiDAR attributes for extracting road median. In Section 2, we describe a step-wise description of our road median extraction algorithm. In Section 3, we test our algorithm on two road sections, demonstrating the successful extraction of distinct types of road medians. Section 4 discusses the test results of road median extraction and finally, we conclude our paper in Section 5.

2. ROAD MEDIAN EXTRACTION ALGORITHM

Our algorithm is based on the fact that LiDAR elevation and intensity attributes can be efficiently utilised to extract the road median. We input *n* number of LiDAR data sections (50m width; 50m length; 5m height) and road polylines in the algorithm. The dimensions of input data sections were selected empirically as they impact the process efficiency in terms of computational cost. The road polylines, obtained from National Road Authority (NRA), were representing centre, left-lane and right-lane of the dual carriageways in Ireland. Each road polyline was associated with Route ID, Road Number, Direction, Section Number and Lane Representation. A workflow of the road median extraction algorithm is shown in Figure 1. In the following sections, we describe various processing steps involved in our algorithm.

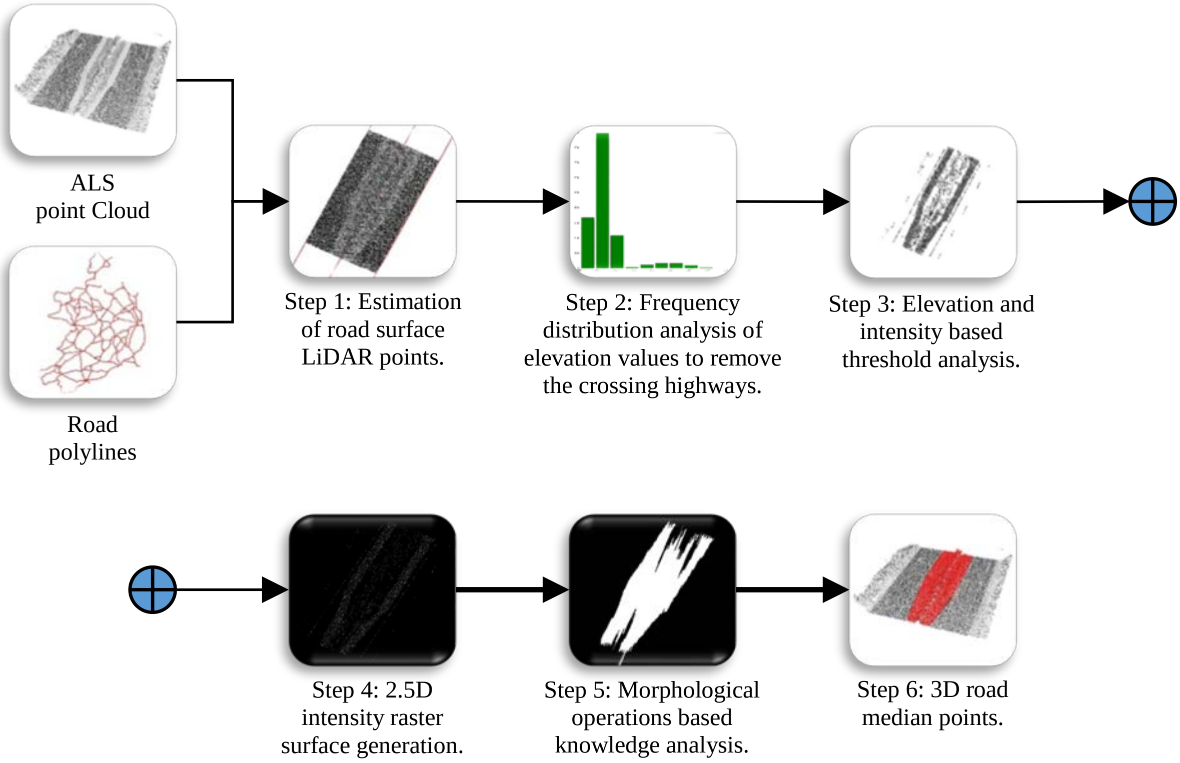


Figure 1: Road Median Extraction Algorithm.

2.1 Road Surface Estimation

In Step 1 of our algorithm, we use the road polylines to estimate the LiDAR points belonging to the road surface. We consider the polylines along the left-lane and the right-lane, and find their intersection with the convex hull fitted to the input LiDAR points. The intersected boundary points are then used to remove the outside points, while inner points are retained which belong to the road surface. Thus, the use of road polylines is efficient in terms of reducing the search space in LiDAR data for extracting the road median. The process of estimating road surface points using road polylines is shown in Figure 2.

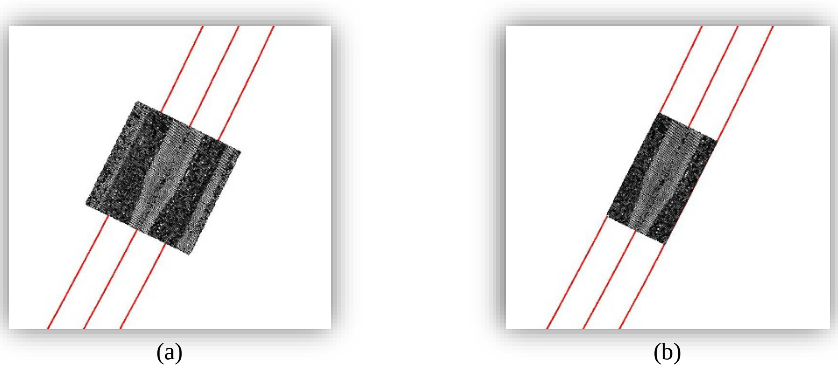
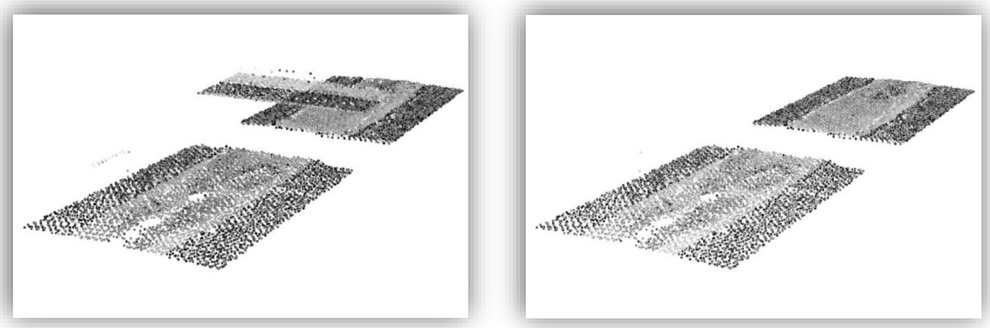


Figure 2: The input (a) road section points and (b) road surface points estimated using polylines represented in red.

2.2 Frequency Distribution Analysis

The road sections consist of highways crossing above them at some locations, which are required to be removed in order to get correct estimation of the road median. In Step 2 of our algorithm, these crossing highways are removed based on frequency distribution of elevation values obtained from the road surface LiDAR points. We assume that along the road section, large number of LiDAR points will belong to its surface, while in comparison less points will correspond to any highway crossing above it. Based on this assumption, frequency distribution of elevation range values is estimated and then elevation value with maximum frequency is identified as h_r, which belongs to the road surface. The points with elevation values more than $h_r+\varepsilon$ or less than $h_r-\varepsilon$ are removed, while in-between points are retained for further processing. The value of ε parameter is estimated empirically and fixed for all the road sections in such a way that it could be useful in removing the crossing highways. In this way, crossing highways above the road sections are removed by detecting the road surface points with maximum elevation frequency. An example of removing crossing highway above the road section is shown in Figure 3.

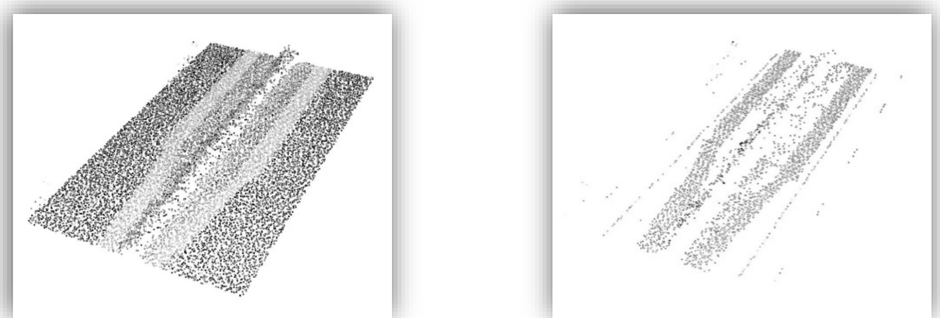


(a) (b)

Figure 3: The road surface (a) with crossing highways above it, which is (b) removed based on frequency distribution analysis of its elevation values.

2.3 Threshold Analysis

In Step 3 of our algorithm, we apply threshold to elevation and intensity attributes in order to get an initial estimation of the road median. The elevation and intensity values are normalised with respect to their global minimum and maximum values, and converted to an 8-bit data type. This enables a two way transformation between the 8-bit values and their original LiDAR values, which in turn will allow for the use of a single threshold value for all road sections. We apply T_{elev} and T_{int} threshold parameters to road surface LiDAR points and get initial road median points, as shown in Figure 4. The values of these threshold parameters are estimated empirically and fixed for all the road sections, which allows for their fully automated application.



(a) (b)

Figure 4: Threshold values applied to the (a) road surface points in order to get an initial estimation of the (b) road median.

2.4 2.5D Raster Surface Generation

In Step 4 of our algorithm, we generate 2.5D intensity raster surface from the initial estimated road median points using a cell size, c parameter. The value of c is selected based on an average spacing of LiDAR points. The value of each cell in the raster surface is estimated as the average of the intensity values of the LiDAR points that fall within the 2.5D boundary of the cell. The intensity values are normalised with respect to their global minimum and maximum, and converted into an 8-bit data type.

2.5 Morphological Operations based Knowledge Analysis

The initial estimated road median may be incomplete and contain other road surface elements that are introduced through the use of thresholding. To overcome this, we make morphological operations based knowledge analysis of road median in Step 5 of our algorithm (Kumar et al., 2014). This analysis involves three processes. In the first process, the intensity raster surface is converted into a binary image and then morphological dilation operation is applied in which a structuring element is placed over the image cells. The purpose of dilation is to use the structuring element to grow cells with a value of 1 in order to fill in any holes. A structuring element consists of a binary matrix that represents the selected shape and size. A central element of the matrix represents an origin and the elements with a value of 1 describe a neighbourhood of the structuring element. The origin of the structuring element is positioned over each cell in the binary raster surface to dilate that cell along the neighbourhood of the structuring element.

We select a linear shaped structuring element to dilate the cells due to linear pattern of the road median. The length, l, of the linear element is selected empirically and is fixed for all the road sections, which allows us to automate the morphological operation in our algorithm. The linear element is used with a θ angle that is calculated from the mean heading of the road polyline points. This angle is useful in dilating the road median cells along the longitudinal direction. The use of dilation operation fills the holes and completes the shapes of road median in the input binary image. An example of the dilation of input binary image using linear element is shown in Figure 5(a).

(a) (b) (c)

Figure 5: Morphological operations based knowledge analysis: (a) dilated image, (b) road surface cells removed and (c) eroded image.

In the second process, we group cells into objects in the dilated image using connectivity. If a cell has a value of 1 then it is connected to the cells whose values are 1 and are directly above, below, left or right of that cell. We calculate the length and average width values of each object in the dilated image. Objects whose length and average width values are less than length threshold, T_L and width threshold, T_W are considered as other road surface elements and are removed from the image, as shown in Figure 5(b). These length and width threshold values are based on knowledge about standard dimensions of the road median. In the third process, we apply an erosion operation to the dilated image in order to retain the original boundary shape of the road median. In an erosion operation, cells are removed from the road median cells using a structuring element. The linear shaped structuring element used for dilation is also applied to erode the road median cells, as shown in Figure 5(c). In this way, the combined use of morphological operations and knowledge about the dimensions of the road median is able to complete its shape and remove other road surface elements.

2.6 3D Road Median Points

In final Step 6 of our algorithm, we extract the 3D road median points from the 2.5D output. We fit a convex hull to the eroded image and extract the initially input 3D LiDAR points, contained within the fitted convex hull. The purpose of fitting convex hull is to estimate proper shape of the road median and extract more dense LiDAR points than extracting from the 2.5D road median image cell boundaries. In the next section, we present the test results of our algorithm on the road sections.

3. EXPERIMENTATION

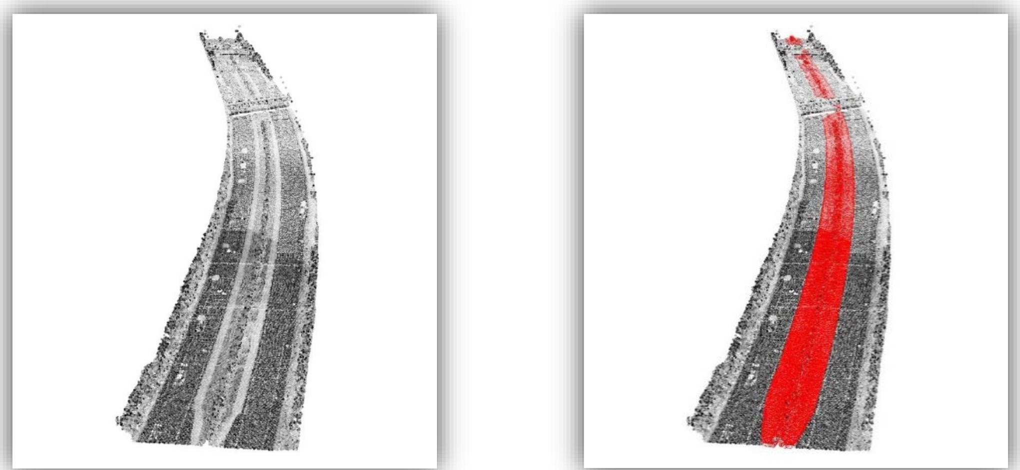
The dataset was acquired using ALS system along dual carriageway in Ireland. We tested our automated road median extraction algorithm on two data sections, which covered 2-Km of dual carriageway. The first 1-Km section of dual carriageway consisted of road median with narrow concrete barrier, as shown in Figure 6(a), while the second 1-Km section contained road median with wide grass-hedge barrier, as shown in Figure 6(b).

(a) (b)

Figure 6: Digital images of the (a) first road section with concrete barrier median and the (b) second road section with grass-hedge median.(geographic locations: (a) 53^{0}21’11”N 6^{0}27’26.1”W (b) 53^{0}26’09.8”N 6^{0}12’37.7”W). (Source: Streetview, Google)

(a) (b)

Figure 7: The (a) first road section points and (b) extracted road median points represented in red.



(a) (b)

Figure 8: The (a) second road section points and (b) extracted road median represented in red.

To process each 1-Km road section, we used *n=20* number of LiDAR data sections (50m width; 50m length; 5m height). We applied our road median extraction algorithm to each road section using empirically estimated parameters. The value of ε was selected as 4m, which was found to be useful in removing the crossing highways above the road sections. The threshold parameters, T_{elev} and T_{int} were applied as 200 and 100 respectively, within 8-bit data type range, to get initial estimation of medians in both the tested road sections. The cell size, $c=0.1$ was used to generate 2.5D intensity raster surface from initial estimated road median points. The length, l of linear element was used as 50, while θ angle was calculated from the mean heading of the road polyline points. The length threshold, T_L was applied as 100 in both the road sections, however due to different width size of medians, we applied different values of T_W in them. The value of T_W was provided as 5 in the first road section, while in the second section it was applied as 10. The final extracted road medians in the first and second road sections are shown in Figure 7 and 8 respectively.

4. RESULTS & DISCUSSION

Our automated algorithm was able to extract distinct road medians in two tested road sections. The first road section consisted of median with narrow concrete barrier, while in the second section, the road median was based on wide grass-hedge barrier. In both the cases, the applied approach was successful in extracting the distinct road median objects. The tested road sections were also associated with highways crossing above them at some locations, which were efficiently removed based on frequency distribution analysis of elevation values. This analysis was done based on an assumption that large number of points will belong to the road surface in comparison with crossing highways. However, in case of wider highway, the large number of LiDAR points will belong to it and this will lead to the removal of road section beneath it. In the morphological operations, we applied different values of width threshold due to different width of the medians in the tested road sections.

The road medians at some locations along the tested road sections were missed, while at other locations, the adjacent lane markings were included in the output as false positives. High reflectivity from the lane markings led to their inclusion in the initial estimated road medians during threshold applied to the intensity attribute. Further, their close proximity to road median did not enabled their removal during morphological operations. The value of LiDAR intensity attribute depends upon incidence angle of the laser pulse, the distance from the laser scanner and the illuminated surface. The normalisation of intensity attribute with respect to these factors will provide the reflectance values from the targeted objects. The use of such normalised intensity values will improve the process of road median extraction. The fitting of convex hull was useful in terms of estimating proper shape of the road median and in extracting more dense LiDAR points. However, in some cases of non-continuous medians along the road section, they were falsely extracted as continuous.

5. CONCLUSION

In this paper, we presented an automated algorithm for extracting road median from ALS dataset. The developed algorithm was developed based on the assumption that LiDAR data provides elevation and intensity values, which can be utilised to extract the road median. The use of road polylines enables to estimate the points belonging to the road surface, which in turn facilitates more accurate extraction of road median. We make the frequency distribution analysis of elevation values, which provides to remove the highways crossing above the road sections. The morphological operations based knowledge analysis is useful in completing the shape of road median and removing other road surface elements, that are introduced through the use of thresholding. The algorithm was successfully tested on two road sections to extract the concrete and grass-hedge based road medians. The developed approach provides reliable and precise information about the location and condition of road median objects. This information can assist road authorities in ensuring rapid and timely maintenance of road medians, that constitutes as one of the fundamental feature along the route corridor environment.

In future work, the algorithm will be tested on road sections with more distinct medians. The extracted road median objects will be qualitatively verified using an efficient validation approach. The elevation and intensity threshold values applied to get an initial estimate of the road median, were estimated empirically. However, more robust and automated approach will be developed in order to get the threshold values. Focus will also be on optimal use of convex hull so that proper shape of even non-continuous road medians could be estimated. The size of input data sections and cell size of raster surfaces impact the efficiency of our algorithm in terms of computational cost. These parameters are required to be efficiently analysed to find their optimal values. Future work will also focus on the integration of our algorithm with 3D geospatial database management system to enable its large-scale implementation.

ACKNOWLEDGEMENTS

The authors would like to acknowledge National Road Authority (NRA), Ireland for providing ALS dataset under the research program SFI07/SRC/I1168; BU270182. The presented work also received support through the research grant SFI13/IF/I2782. The authors gratefully acknowledge this support.

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