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RIVER EMBANKMENT IDENTIFICATION IN THE AIRBORNE LASER SCANNING POINT CLOUD

PRZEMYSŁAW TYMKÓW, ANDRZEJ BORKOWSKI, PIOTR GOŁUCH

Institute of Geodesy and Geoinformatics, Wrocław University of Environmental and Life Sciences, ul. Grunwaldzka 53, 50-357 Wrocław. E-mail: tymkow@kgf.ar.wroc.pl, borkowski@kgf.ar.wroc.pl, piotr.goluch@up.wroc.pl

Abstract: Hydrodynamic modeling is one of the most significant tools in risk and environmental management of floodplains. Such research requires precise and reliable digital terrain models (DTM). Moreover, DTMs should determine the location of terrain edges for the area of river valley, i.e. river embankments. Terrain models are usually built using data collected with airborne laser scanning. Irregular cloud of scanned points can be used for 3D line edges modeling. However, this task is difficult because determination of the river embankment edges is not always exact; the edges are not defined precisely or they can be hidden in bushes and groups of higher vegetation. One of the newest methods of the edges modeling relies on the intersection of two planes. The main issue here is to classify points into subsets located on both sides of the modeled edge. In this study, the algorithm employing multilayer feed-forward neural network for point classification is presented. It allows us to include a priori information about the expected shape of surface as well as the orientation of embankment with respect to the river flow direction. Classification was performed on the real airborne laser scanning dataset. Confusion matrix was used for the quantitative accuracy assessment. This matrix was built for the test vector based on the comparison of the obtained results with an interactive sample.

1. INTRODUCTION

In many environmental studies such as generation of hydrodynamic models for rising discharges information about the lay of the land is essential. Current hydrodynamic models based on a 2D discharge specification use a geometry description of a high water riverbed which has a form of DTM. Requirements imposed on the accuracy of mapping the area shape, which depends both on measurement accuracy and the number of survey points, make airborne laser scanning a very popular technology for acquisition of data used to generate DTM. The outcome of laser scanning is a set of irregularly distributed points $\{x, y, z\}$. DTM generation using such a point cloud requires filtration in the first stage, which means indicating points that belong to the surface, and then a model generation out of these points in the second stage. As far as for relatively small DTM resolutions (namely, in the range of a dozen or several dozen metres) common algorithms give good results of the actual surface approximation on the accepted generality level, in the case of a precise model with a resolution around 1 metre these algorithms result in the loss of information concerning break lines for such areas as flood embankments. Generation of a reliable hydrodynamic model still requires inclusion of this information. Geometric information on river embankments is included directly in the laser scanning data set and facilitates embankment modelling in the vector format. This modelling consists of two stages. In the first stage, points belonging to particular surfaces of the embankment have to be identified. Properly classified points are fundamental for 3D modelling of the embankment edges. The first stage plays a crucial role in the modelling of break lines. Errors committed at this stage impinge on the modelling outcome. At the same time, this stage is the most difficult one, both in terms of the solution uniformity and automation of the whole process. Further on, we focus mainly on issues related to the first stage of modelling. Only an outline of the second stage is given in this study.

2. MODELLING OF DTM BREAK LINES IN HYDRODYNAMIC MODELLING ISSUE

In engineering the modelling of break lines, for instance, of a flood embankment, is performed by manual digitisation of this embankment and by allowing this information in a hydrodynamic model. Such an approach is very laborious and in afforested areas, where digitisation on the basis of ortophotos and satellite images is not possible, the modelling process which uses a cloud of survey points is the only solution.

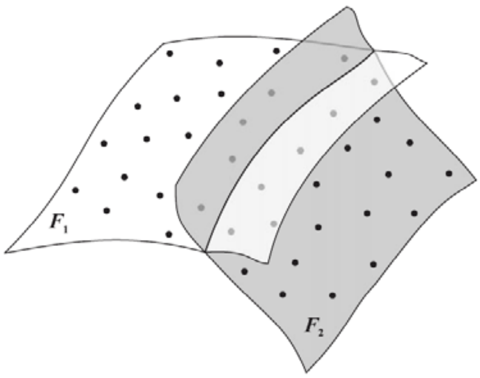

Fig. 1. Edge modelling as an intersection line of two surfaces

Edge modelling using the airborne laser scanning data requires high scanning resolution, which should be at least 1 point per square metre. Edges are usually modelled as 3D vectors based on information about points obtained from laser scanning or as 2D vectors using secondarily processed data. The initial attempts used the latter approach and involved interpolation of elevations on a regular grid and through methods for digital processing of edge identification images, e.g., by means of edge filters. Such attempts are performed by BRÜGELMANN [1] and SUI [2]. The 3D approach is more recent and depends on determining the edge as an intersection line between surfaces situated to the left and right of the break line in a small area [3] or as an intersection line of two surfaces [4], [5].

The idea of this solution is shown in figure 1. The two approaches require preliminary classification of points to those that are situated to the left and to the right of the predicted location of the modelled break line. The key issue in break line modelling using laser scanning data consists in extracting from the whole data set those points which are important for edge modelling. These are the points that belong to relevant surfaces.

3. AIRBORNE LASER SCANNING DATA CLASSIFICATION

Classification of survey points with respect to their belonging to relevant surfaces is hindered by a number of data-related factors. The airborne laser scanning data features not only the aforementioned irregularity, but also varied density related to changes of the beam incidence angle caused by inclination of the surveying platform or the scanning technology itself (rotating mirror in some measuring instruments). Furthermore, the outcome of scanning is usually a series of overlapping scans, which results in a double increase of point density in overlapping strips. The other obstruction is caused by the features which determine whether or not a point belongs to a relevant surface, and which are not directly assigned to the point that is subject to classification but result from its surroundings. Such a situation requires an analysis of a certain data context and excludes the punctual approach. It interferes with application of methods for digital processing of images, such as data clustering.

The starting point for developing classification algorithm discussed in this research is the analysis of land use recognition by men using laser scanning data visualisation. An operator who digitises the location of a flood embankment has some a priori knowledge, such as:

- expected shape of river embankments,
- orientation in respect of river location,
- approximated distance between the river and embankments.

These features can be considered in automatic classification process. By watching the visualisation of point cloud, man recognizes land uses in the image on the basis of the context. Data, although irregular, are ‘regularised’ on the retina. The human brain as a classification tool can generalise knowledge. An algorithm which follows the aforementioned features of a human as a classifier is an artificial neural network.

2.1. ARTIFICIAL NEURAL NETWORK AS A CLASSIFIER

Neural network classifier has the following characteristics:

- works as a contextual memory,
- learns by examples,
- generalisation ability,
- fail-safe,

• parallel processing,
• non-algorithmic processing.

The network is provided with information that needs to be classified. It is a feature vector corresponding to a point that is subject to classification. In this case, the vector is composed of point elevations in the surroundings that have already been regularised. A full analogy to visual observation can be noticed. In the first stage, the neural network topology, viz. the size of hidden layers, should be determined. Then, using the specialist knowledge which consists of examples of correct classification, the training of the network takes place. The data set S under training is an N-element set of objects, where each of the objects is described by a feature value vector x_i and an encoded number of the class j_i:

$$S = \{(x_1\ , \ j_1), (x_2, \ j_2), \ldots, (x_N\ , \ j_N)\}\,. \tag{1}$$

The process of neural network learning is analogous to training of an operator who carries out manual digitisation. When training is completed, the neural classification can be used for recognition of objects with similar features to the examples included in the training set. The scheme of this process is shown in figure 2. Hence, the selection of representative examples is a key problem.

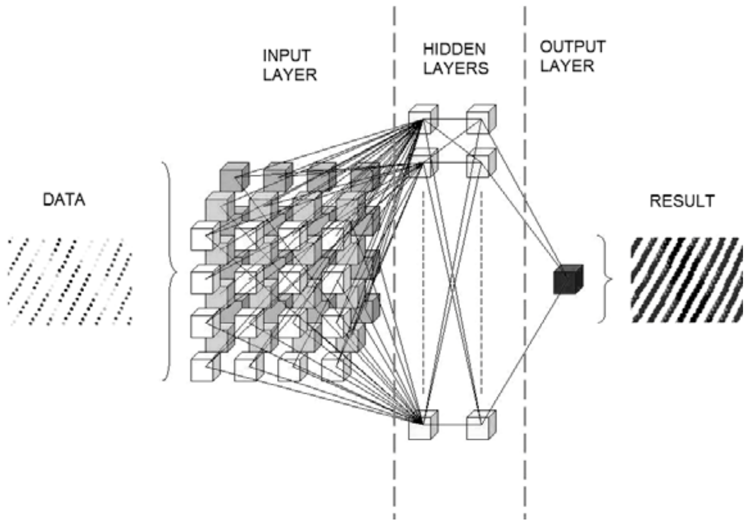

Fig. 2. Scheme of airborne laser scanning point classification process using neural network

2.2. PROCESS OF RIVER EMBANKMENT IDENTIFICATION IN LASER SCANNING POINT CLOUD

In order to prepare a learning set, the classifier needs to manually indicate the membership of particular points in appropriate classes using digitisation. After that, the river axis is indicated which allows for inclusion of information on the structure orientation which is more or less parallel to the watercourse (figure 3A). In the future, this stage based on the manual digitisation of the watercourse axis will be automated. It is expected that the active contour model (snake) will be used in this task [6].

The next stage consists in orienting the context (mask) for each of the survey points by calculating the shortest distance to each of the lines determined by sections of the watercourse axis and selecting as the direction of the x-axis of a local coordinate system such a perpendicular line whose intersection point is situated on the nearest section of the watercourse axis (figure 3B). On the basis of the mask size and density assumed at the beginning of the research, coordinates of points of each mask mesh are calculated in a working (e.g. national) coordinate system through isometric transformation from a local coordinate system (figure 3C). If the perpendicular to the lines determined by sections of the watercourse axis for the point under consideration does not have any intersection point with the watercourse section, such a point is classified at this stage as belonging to the set of points which are not members of the "embankment" class. The next stage depends on assigning the feature value, namely the elevation to individual mask points. This is done through quantization. The weighted mean is calculated for all points situated in the radius which equals half of the mask density. This does not exclude existence of the mask meshes to which no values have been assigned and thus interpolation is not necessary.

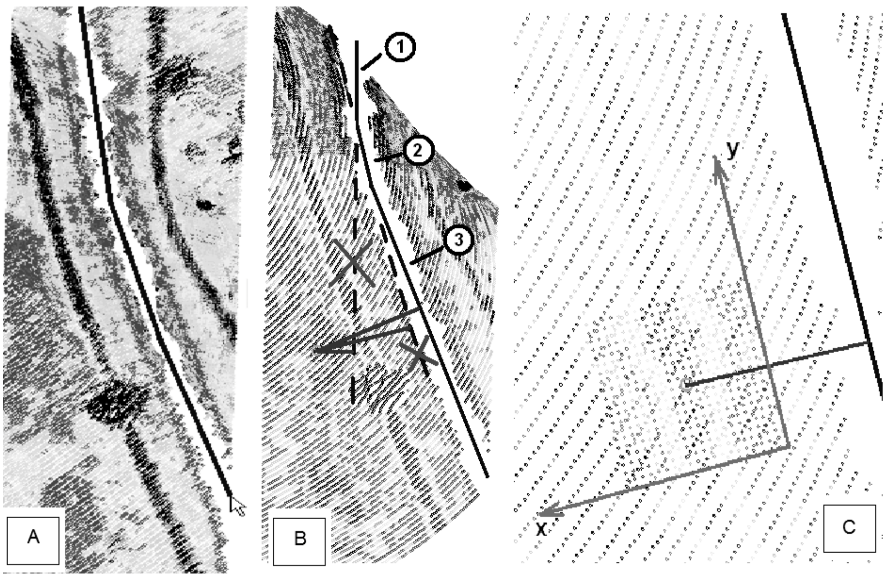

Fig. 3. Stages of the river embankment recognition process:
A – digitalization of the watercourse axis, B – mask orienting, C – local (mask) coordinate system

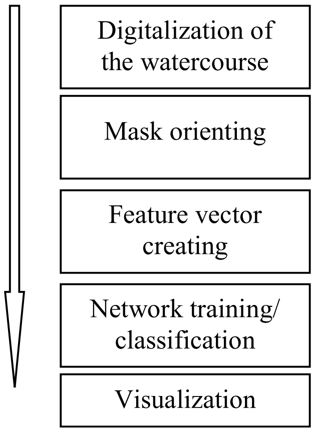

Fig. 4. Abridged scheme of river embankment identification method

The last step is subtraction of minimal elevation within the mask from the calculated means. The number of mask meshes specified by the resolution and the size determines the size of the entrance layer of the neural network. Owing to a classification standard, the network training takes place. The trained network may be used for recognition of laser scanning with similar parameters on the basis of any data set. The result is visualized using a colour palette. An abridged scheme of this method is shown in figure 4.

3. EXAMPLES OF RECOGNITION

The efficiency of the point classification algorithm was investigated using an example of the Widawa river flood embankment recognition close to its estuary to the Odra river. The prototype ScaLars II laser scanner provided laser scanning data [7], [8]. The scanning resolution was 2 up to 3 points per square metre. The distances between adjacent points in a single scan are about 0.6 m. For test purposes three fragments of the point cloud were used: the learning set (figure 5A) and two test sets (figure 6A and 6B). The test set 2 featured diversified densities of survey points in comparison with the learning set which resulted from the overlapping of two scans. Manual digitisation facilitated recognition of points that belong to the "embankment" class in the learning set (figure 5B). This knowledge was used for training the neural network. A three-layer, unidirectional neural network with nine hidden neurons was used. The network was trained with standard back propagation method. The trained network was used for classification of test sets. The results are shown in figure 6B and 7B.

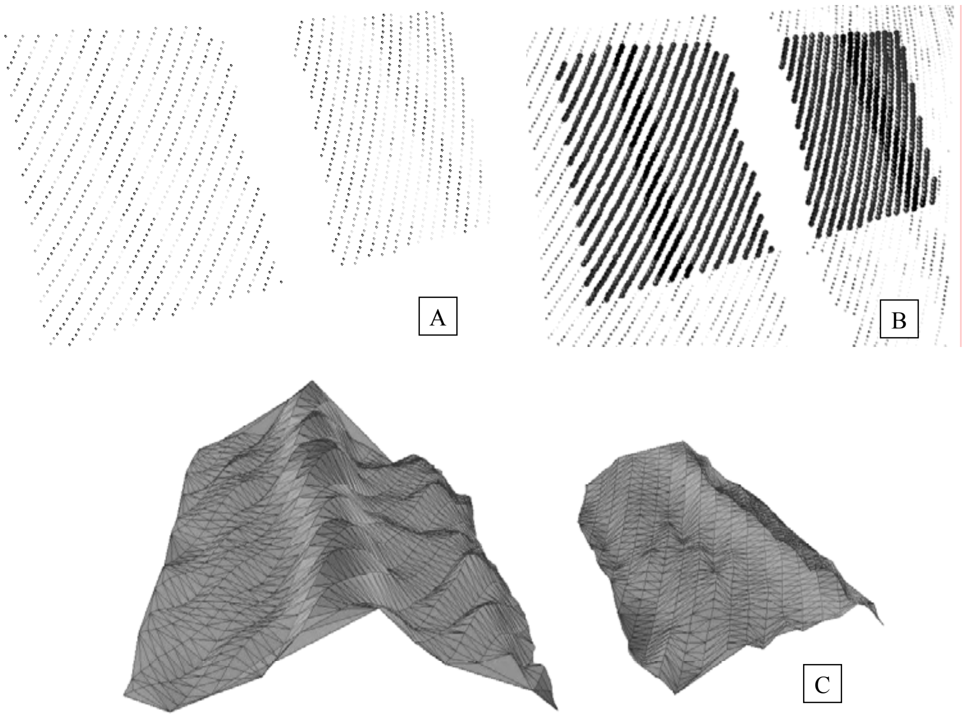

Fig. 5. Training set: A – airborne scanning data, B – classification pattern
made by manual digitalization C – digital terrain model

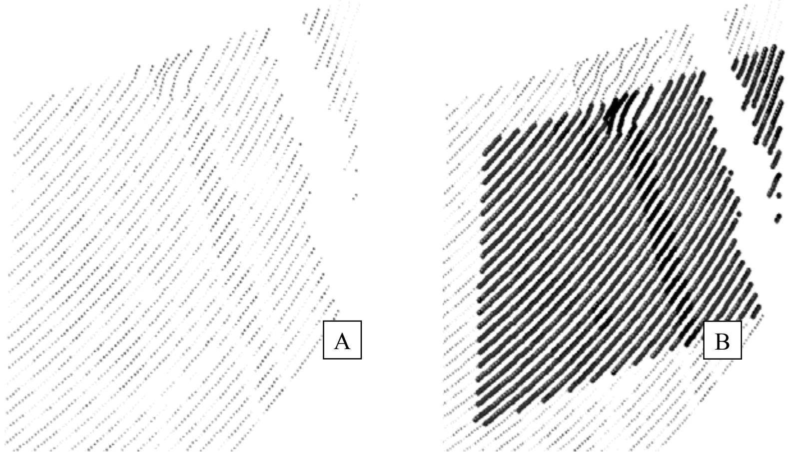

Fig. 6. Recognition result of training set 1:
A – data, B – visualization of classification result

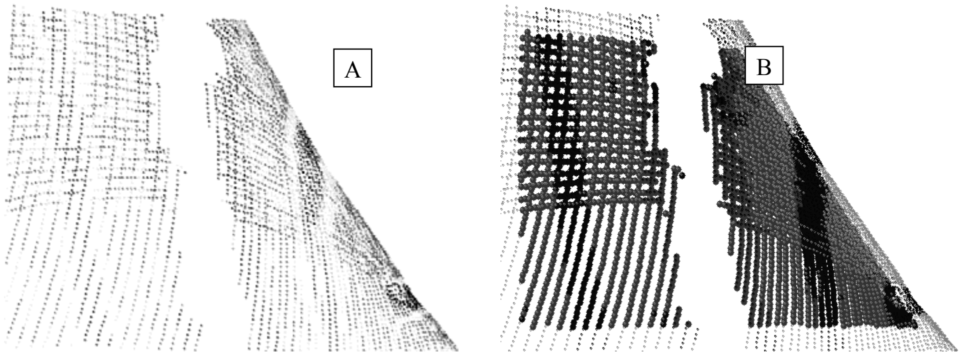

Fig. 7. Recognition result of test set 2: A – data, B – visualization of classification result

3.1. QUANTITATIVE MEASURE OF RECOGNITION ACCURACY

Different measures can be used for the classification quality description. In literature (eg. [9]), the confusion matrix $\mathbf{A} = [a_{ij}]$ method is recommended where a_{ij} is the number of points from the j-th class that have been classified as belonging to the i-th class. The confusion matrix has the following structure:

Table 1

Confusion matrix [10]

Belongs to class		Pattern			
		1	2	…	M
Recognition result	1	a_{11}	a_{12}	…	a_{1M}
	2	a_{21}	a_{22}	…	a_{2M}
	…	…	…	…	…
	M	a_{M1}	a_{M2}	…	a_{MM}

When considering two classes the confusion matrix has the structure:

Table 2

Confusion matrix for dichotomy problem [10]

Belongs to class		Pattern	
		1	2
Recognition result	1	a_{11}	a_{12}
	2	a_{21}	a_{22}

The quantitative accuracy measure for test set 1 indicates that 91.5% of points were classified correctly. The percentage of correctly classified points in class “embankment” was 85.1%. The confusion matrix for test set 1 is shown in table 3.

Table 3

Confusion matrix for test set 1

Belongs to “embankment” class		Pattern	
		YES	NO
Recognition result	YES	137	161
	NO	24	1846

In the case of test set 2 the number of overall points was 3323. There were 3053 (91.87%) correctly classified points. The percentage of correctly classified points in class “embankment” was 94.9%. The confusion matrix for test set 2 is shown in table 4.

Table 4

Confusion matrix for test set 2

Belongs to “embankment” class		Pattern	
		YES	NO
Recognition result	YES	595	238
	NO	32	2458

4. CONCLUSIONS

The present method of laser scanning point classification for the need of edge modelling in DTMs may be used with minor alterations for recognition of different types of land use (e.g. slopes, ditches). The characteristic feature is the feasibility of classification when density of survey points is varied. In this research, preliminary results of the suggested method verification are discussed. The classification accuracy obtained is around 91%, which is found to be satisfactory. Errors which are caused by individual, misclassified points, especially on the borders of the area under study, can be easily eliminated in the process of edge modelling. The classification errors in the case of points situated close to the modelled edge are hazardous. The algorithm will be developed by adding generalization mechanisms (knowledge generalization) and automated by adding a module for automatic recognition of the watercourse axis.

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