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Extracting urban features from LiDAR digital surface models

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Abstract

The use of airborne Light Detection And Ranging (LiDAR) technology offers rapid high resolution capture of surface elevation data suitable for a large range of applications. The representation of both the ground surface and the features on that surface necessitates the removal of these surface features if a ground surface Digital Elevation Model (DEM) product is to be produced. This paper examines methods for extracting surface features from a Digital Surface Model (DSM) produced by LiDAR. It is argued that for some applications the extracted surface feature layer can be of almost equal importance to the DEM. The example of flood inundation modelling is used to illustrate how a DEM and a surface roughness layer could be extracted from the original DSM. The potential for refining surface roughness estimates by classifying extracted surface features using both topographic and spectral characteristics is considered using an Artificial Neural Network to discriminate between buildings and trees. © 2000 Elsevier Science Ltd. All rights reserved.

Keywords: LiDAR; Digital Surface Model, DSM; Digital Elevation Model, DEM; Filtering; Feature extraction; Flood inundation modelling

1. Introduction

Digital Elevation Models (DEMs) have varied and well-documented applications (Burrough & McDonnell, 1998) including visual impact assessment, hydrological modelling, flood prediction and site suitability analysis. The automated creation of elevation models from remotely sensed data can offer a representation of both the ground surface and the objects on that surface. Such representations, often termed

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Digital Surface Models (DSMs) offer the possibility of extracting the elevations of surface features to leave the ground surface DEM. For many applications in the urban environment this separation of above-surface feature information from ground information can offer a useful combination of data sets. For example, detailed knowledge of the elevation of the ground surface is essential for predicting flood inundation and the potential effects of sea level rise, whilst a detailed model of the man-made objects that would be affected is essential for property owners, planning authorities and insurance companies. This paper discusses several such applications and focuses on how Airborne Laser Scanning devices can provide digital surface models which can be used to separate surface features from the ground for modelling flood inundation from rivers in urban and semi-urban environments.

DEMs can be constructed by digitising existing topographic maps (Gao, 1995, 1997) or by using stereoscopic aerial photographs. With the advance of digital photogrammetry, DSMs can be created using stereo image matching techniques (Smith & Smith, 1996). Many authors (Abanmy, Khamees, Scarpace & Vonderohe, 1995; Jaafar & Priestnall, 1998) have considered the potential for these DSMs to provide the heights of surface features such as buildings.

Recently LiDAR (Light Detection And Ranging) has become an established technique for deriving geometric information in three dimensions. The system is seen to offer a relatively quick technique for extracting accurate surface models and thus offers the potential for the creation of DEMs and other mapping products (Kost, Loddenkemper & Petring, 1996; Lohr, 1998). LiDAR is considered to offer several potential benefits for the creation of DSMs:

1. Offers a cost-effective way of producing DSMs with an accuracy in the order of decimetres (Lohr, 1998), and is less prone than other remote measuring systems to difficulties in measurement due to variations in weather.
2. Offers precise definition of surface features through a very high density of recorded points, allowing the creation of gridded DSMs with cell resolutions of 1–3 m (Lohr, 1998). Automatic DSM generation using digital photogrammetry has problems with feature definition because of surface smoothing and the difficulty of controlling the image-matching algorithms (Smith, 1997; Smith & Waldram, 1996; Smith, Smith, Tragheim & Holt, 1997).

Reliable and accurate three-dimensional models of the urban environment are required by many applications and constructing these models has been an active research field involving a diversity of approaches using remotely sensed data (Gruen, Baltsavias & Henricsson, 1997). A comparison of photogrammetry and LiDAR (Baltsavias, 1999) considers these technologies not merely competitive but complementary and suggests that their close integration should be encouraged. Nevertheless, the production of DSM products using LiDAR is a quicker, more automated process and coupled with the high density of point measurements can offer greater definition of urban features, these factors encouraging research into the automated extraction and characterisation of surface features.

The degree to which precisely defined surface features need to be extracted and categorised depends upon the application. The reconstruction and visualisation of three-dimensional urban models, for example, requires precise definitions of building walls and roofs and much research effort has focused on their automated extraction (Gruen, Kubler & Aqouris, 1995). Typically, utilising raw laser data or 1-m DSMs, buildings have been identified, removed and replaced with Computer Aided Design (CAD)-generated building objects, often with the aid of existing building outlines or through the use of additional optical information (Haala & Brenner, 1997, 1999). With CAD objects placed on the DEM surface, textures can be mapped onto individual faces of these objects giving the high levels of photo-realism necessary for many urban planning visualisation exercises.

For land use change detection the incorporation of building heights offers important extra information over and above that offered by optical sensors alone (Priestnall & Glover, 1998). Change detection between map vector outlines and building edges from newer imagery may be possible under certain conditions but processing can be complex. Due to the nature of gradient maps derived from the LiDAR data, as shown in Fig. 1, the identification of building edges becomes possible. Although not sensitive to lighting conditions, as are edges extracted from optical sensors, edge extraction from laser data is complicated by the presence of objects in close proximity to buildings such as parked vehicles and trees. Land use-change detection need not, however, rely upon the recognition of individual surface features. As the capture of laser data becomes more routine and time-series data sets become available, then difference

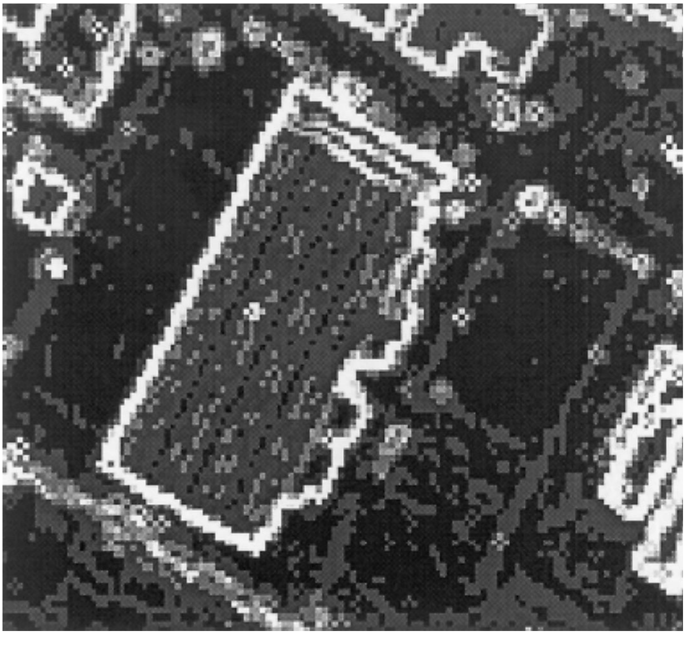

Fig. 1. Detail from a slope map derived from a LiDAR Digital Surface Model (DSM), the brighter cells representing steeper slopes.

maps produced by subtracting successive DSMs should prove a successful means of urban change detection without the requirement to recognise features at every stage (Murakami, Nakagawa, Hasegawa, Shibata & Iwanami, 1999).

For certain applications the extraction of discrete geometrically precise objects is less important than the separation of the surface feature layer from the underlying ground elevations. Laser scanning can offer a fast, cost-effective alternative to conventional methods of producing DEMs from digitised contours or stereo plotters. One application for which an accurate DEM is important is the modelling of flood inundation from rivers. For flood hazard mapping over large areas ground DEMs derived from contour data are often used, but for more detailed modelling of flood inundation the use of LiDAR derived surface models can be considered. DEMs created from contour data are reliant upon a suitably small contour interval and a large number of surveyed spot heights in order to represent the ground surface faithfully. For floodplain mapping and modelling, laser scanning offers the chance to represent the ground surface at finer resolutions and, therefore, to predict the extent and depth of flood inundation more precisely (Marks & Bates, 2000). Gomes Pereira and Wicherson (1999) consider the potential of LiDAR for supplying topographic data for the management of fluvial zones. A simple simulation of river flooding using a LiDAR DSM where objects impacted by the flooding are clearly seen is shown in Fig. 2. Models of flood inundation can be one-dimensional where cross-sections extend across the floodplain from points along the river channel, each section being assigned a roughness coefficient. Where a one-dimensional model predicts significant floodplain flow a two-dimensional model can be used to give more reliable estimates of flood depth and extent. The floodplain is represented as a triangulated surface where each triangle is assigned a roughness coefficient (such as Mannings *n*) which is typically estimated manually using field or photographic observations (Chow, 1973).

The representation of a more complete and precise coverage of surface roughness coefficients over the flood plain, coupled with a high resolution elevation surface, would offer improved data provision for this modelling process. LiDAR could provide such data if the surface features are removed to leave the ground elevation surface, and in so doing the spatial distribution of surface roughness could be estimated by summarising the texture of the features removed.

2. Rationale

Attempts to separate surface features from the ground elevations work on the assumption that these features are higher than the surrounding surface (Jaafar & Priestnall, 1999; Weidner & Forstner, 1995). If the above-surface features can be identified and removed from the DSM, then the ground elevations for the gaps left by the removed features can be replaced by interpolating between DSM elevation values around the edge of each gap.

To identify the above surface features a 'reference surface' which is lower than the LiDAR DSM can be subtracted from the DSM, leaving a 'residual surface'

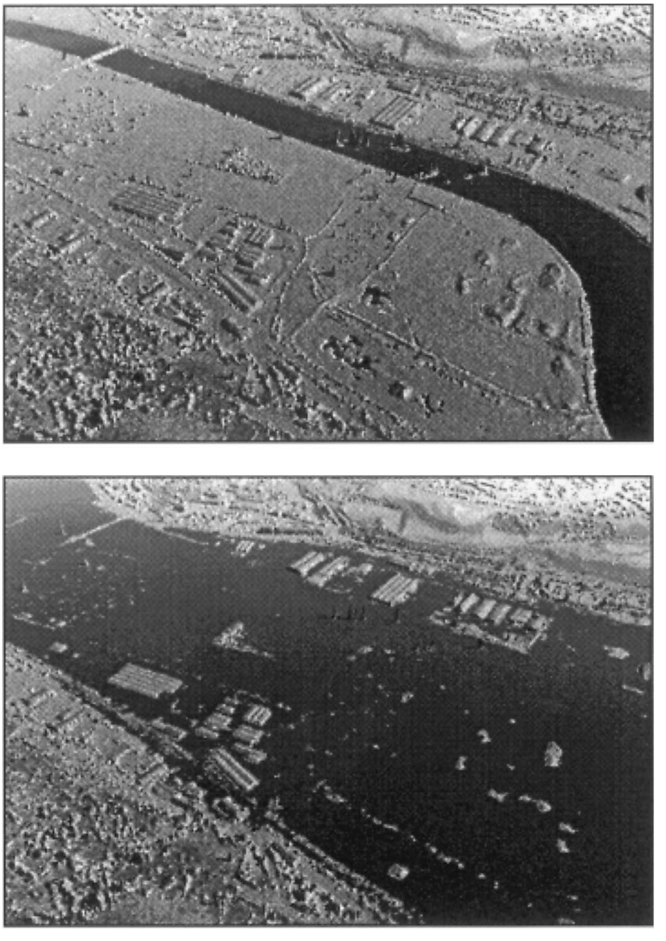

Fig. 2. A simple river flooding simulation using a LiDAR Digital Surface Model (DSM).

representing the locations of all above-surface features. The areas defined in this residual surface can be used to mask out the equivalent areas in the DSM. The final stage involves interpolation to fill in the gaps masked out of the DSM, resulting in the ground DEM.

This study investigates the above procedure with particular emphasis on the creation of a reference surface using a filtering process to smooth the DSM surface. The sensitivity of the results to varying the filter size used was an important aspect of the study. Further discussion of this technique will be outlined in the Methodology section.

Although the isolation of the above-surface features from the ground surface is paramount in this study, the classification of these features based on topographic and spectral character is discussed. The use of an Artificial Neural Network (ANN) to extract features based upon their topographic character alone has been considered (Jaafar, Priestnall, Mather & Vieira, 1999). The most simplistic ANN architecture consists of n inputs connected to a central computational unit and produces one output. The n inputs are summed and a threshold determines whether or not the output is produced (Cawsey, 1998). More complex structures allow several alternative outputs (in this case ground, building or tree) dependent upon the inputs provided. The ability of an ANN to combine inputs derived from a variety of sources and to explore the relative importance of these inputs as discriminators of surface feature types is seen as an important avenue for continuing research.

3. The data

LiDAR is based on sequential laser range measurements from an airborne sensor to points on the ground surface. Knowing the precise position and orientation of the airborne platform, from differential Global Positioning Systems and Inertial Navigation Systems, the laser beam is reflected off the ground surface to enable the three-dimensional positions of the surface points to be determined with decimetre accuracy (Hug, 1997; Söhne, Heinze, Hug & Kälberer, 1993). It is reported that an accuracy of the order of 0.2 m horizontally (x,y) and 0.1 m vertically (z) can be achieved in the production of DSMs (Lohr, 1998) from LiDAR depending on the system used. The nature of the surface models produced allows surface features to be distinctly defined and, consequently, the identification and extraction of these features both as discrete objects and in terms of roughness coefficients becomes a reality.

In this study, the LiDAR data used are those produced by the Environment Agency and the study area is an area of the Trent floodplain at Newark-on-Trent, Nottinghamshire, UK. The study area consists of an undulating topography that includes man-made objects and natural features such as trees. The spacing of the surveyed points is approximately 2.5 m and the final gridded elevation matrices used for analysis have a spatial resolution of 2 m. The DSMs are referenced to the Ordnance Survey of Great Britain (OSGB36) and the heights are transformed to Ordnance Survey Datum Newlyn (OSDN). In the data-acquisition phase, the swath angle used is $\pm 19°$ and the flying height approximately 700 m.

The precise large-scale geometry of building objects as represented in the 2-m DSM (as illustrated in Fig. 1) cannot be extracted reliably but the surface texture is sufficiently well defined to allow the filtering procedure described in Section 2 to be implemented. Although the present study uses the surface topography alone, the availability of multi-spectral remotely sensed imagery offers additional potential for discriminating trees from buildings (Haala & Brenner, 1999) and is the focus of ongoing investigations.

4. Methodology

The task is to separate surface features from ground elevations but the specific techniques very much depending upon the requirements of the application. For example, in the case of three-dimensional urban model reconstruction and mapping it may be appropriate to extract and generalise edges from the gradient image in a similar way to image edges in previous studies (Priestnall & Glover, 1998). Generalised edge features can be grouped to form a candidate building object, supported by height information 'internal to', and 'external to' the building boundary. Techniques such as this rely on high-resolution laser scanning data using either raw point measurements or gridded DSMs with a resolution of around 1 m. For example, Maas and Vosselman (1999) present algorithms to segment individual roof faces of buildings based upon clusters of common aspect values present in the triangulated data set.

The approach taken by the current study does not attempt to extract building geometry but focuses upon extracting the whole surface feature layer with a view to characterising the features present. Several approaches to 'stripping' this surface feature layer have been investigated. The Environment Agency, Bath, UK, have explored the potential of using 3×3 variance filters to identify areas above a certain threshold limit equivalent to a variance of 2 m (or 66.6° gradient). These areas are buffered and the resulting mask is used to remove areas of the DSM which are replaced by re-interpolating elevations across the gaps.

This study presents a modified approach for isolating surface features. Working on the assumption that man-made objects and natural features stand above the surrounding surface a lower reference surface can be subtracted from the DSM, leaving a residual surface representing all surface features (Jaafar & Priestnall, 1998, 1999; Weidner & Forstner, 1995). An important issue at this point is the method used to create the reference surface. In the first part of the investigation, the effects of filtering on the LiDAR DSM using a mean filter of varying size are investigated with a view to deriving the most appropriate smoothed 'reference' surface. The standard deviations (σ) for the derived surfaces are then computed for comparative purposes. The main aim of this filtering exercise is to understand the smoothing effects of the DSM in the creation of the reference surface. As would be expected the value for σ decreases with respect to the filter size used, as shown in Fig. 3.

Choosing an appropriate filter size based upon this effect alone would be difficult. In order to assist the choice of filter size the effect must be understood with respect to the features on the DSM being smoothed. To achieve this an unsupervised classification of the DSM elevation data is carried out. This process of thresholding results in a pre-defined number of clusters, in this case five clusters being assigned to

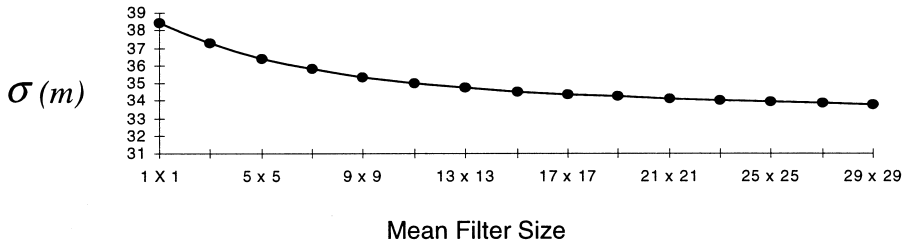

Fig. 3. Standard deviation (σ) with respect to mean filter size.

ensure the separation of the three main entities (the terrain surface, buildings and trees). The choice of the number of clusters varies according to the range of elevation values in the DSM and the number of entities to be differentiated. The polygons created as the result of the unsupervised classification are shown in Fig. 4.

In order to understand the effect of various sizes of mean filters on the smoothing of features on the LiDAR DSM, well-defined regions generated by the unsupervised classification that represent trees, buildings and bare land are randomly identified. In this study, the sample sizes for trees, buildings and bare land regions selected are 32, 33 and 6, respectively. The mean σ for regions of each type are then computed using a range of filter sizes. The effect on σ for trees, buildings and bare land corresponding to various mean filter sizes is shown in Fig. 5.

From Fig. 5, it is found that the σ for polygons representing trees and buildings has a pronounced response as the filter size increases. In general, the mean σ for the tree and building polygons decreases steadily from approximately 5 to 2.5 m and from 9 to 2 m, respectively. However, for the polygons representing bare land, an increase of 4–6 m is experienced. Therefore, referring to Fig. 5, the 'threshold' to differentiate between bare land cover and 'above' surface features could be identified. The 'reference surface' which is lower than the LiDAR DSM could be created using any mean filter with window sizes between 11×11 and 25×25. In this study the 11×11 mean filter is applied to the LiDAR DSM to generate the 'reference surface'. The 'reference surface' is then subtracted from the LiDAR DSM to isolate the above-surface features. As a result of the subtraction, the above-surface features are revealed as scattered regions (Jaafar & Priestnall, 1999) with positive elevation values. However, it should be pointed out that the whole area corresponding to a particular above-surface feature is not necessarily revealed after the subtraction. The cross-section for a selected profile which depicts the effect of the subtraction between the 'reference surface' and the LiDAR DSM is shown in Fig. 6.

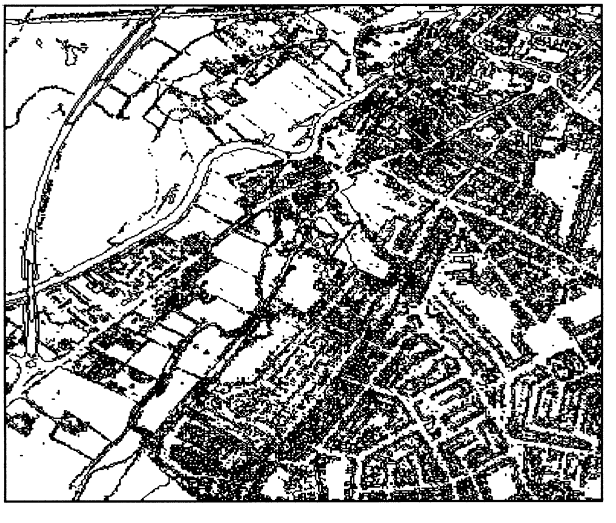

Fig. 4. Polygons created from the unsupervised classification.

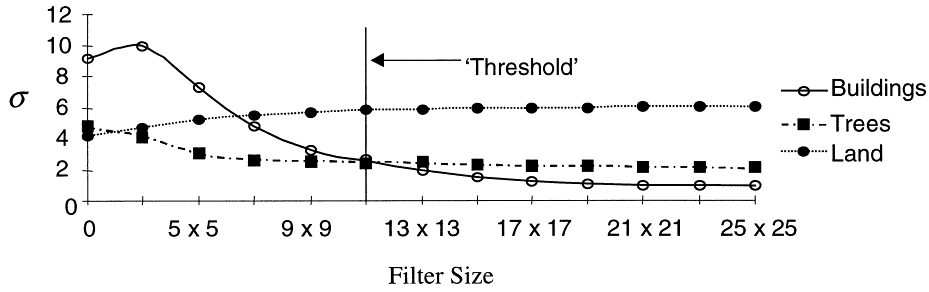

Fig. 5. The effects on standard deviation (σ) with respect to filter sizes for different feature types.

Referring to Fig. 6, it may be seen that part of the above-surface feature may not be revealed as positive elevation values as a result of the subtraction between the 'reference surface' and the LiDAR DSM. This is due to the elevation for the 'reference surface' being higher than the LiDAR DSM near building edges as a result of the smoothing process. This will result in negative elevation values for certain areas in the residual surface. In order to minimise this effect, a 2-m buffer zone is generated surrounding all the detected regions. The choice of a 2-m buffer in this study relates to the grid resolution used relative to the general density observed in the urban features in this area. However, there might be cases (such as large buildings) where the 2-m buffer is insufficient to account for this boundary effect. Therefore, to enhance the detection procedure of surface features, areas with gradients in excess of 50° are extracted and a mask is created in combination with the buffer zone. Finally, the DEM is constructed by replacing DSM elevations coincident with the mask with 'no data', and interpolating across the gaps, the overall approach being summarised in Fig. 7.

The original LiDAR DSM and the derived DEM are shown in Fig. 8. The effectiveness of this process in terms of reproducing an 'accurate' DEM is not

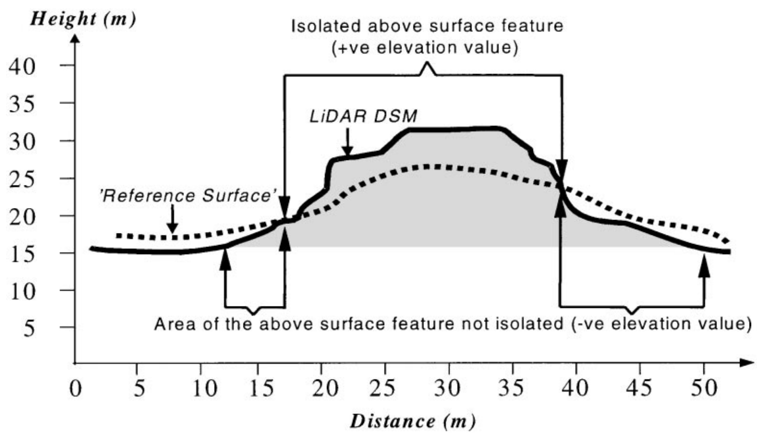

Fig. 6. The effect of subtracting the 'reference surface' from the LiDAR Digital Surface Model (DSM).

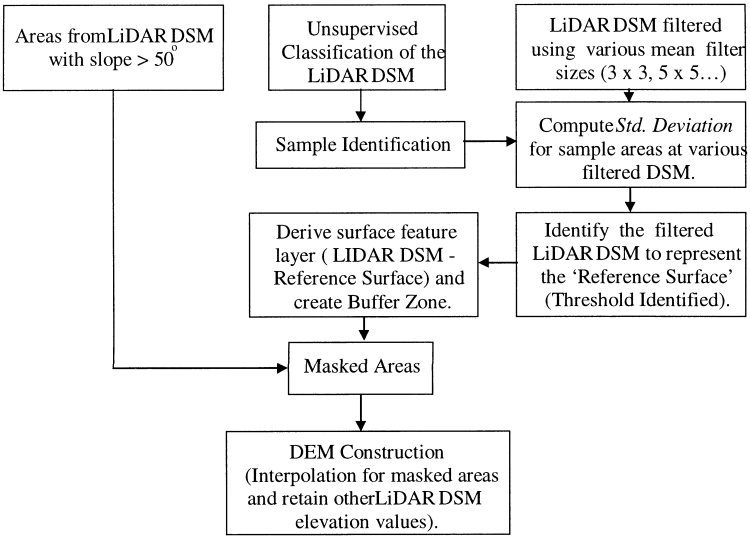

Fig. 7. Outline methodology for constructing the Digital Elevation Model (DEM) from the LiDAR Digital Surface Model (DSM).

investigated in this study; however, techniques to evaluate the sensitivity of the resulting DEM to various filtering procedures is discussed in Jaafar et al. (1999).

For certain applications the derived DEM may be the only data set required; however, the extracted surface feature layer offers useful additional information for many applications. For example, the management of fluvial zones can require modelling of flood flow from rivers and the prediction of the extent, depth and duration of water on the floodplain. Two-dimensional hydraulic models typically represent the floodplain using a mesh of triangular units, incorporating ground surface elevation as a basis for predicting the extent and depth of flood inundation. In addition a roughness coefficient is attributed to each triangular unit. The high density of LiDAR measurements not only offers higher resolution elevation data for floodplain modelling but provides a source of high-resolution surface roughness information. Conventional methods of estimating roughness parameters such as Mannings *n* (Chow, 1973) involve the potentially time consuming task of manual approximation based upon observation of the general character of the surface, often for large triangular spatial units. A map of classified bands of surface roughness, as shown draped over the DEM in Fig. 8, is a simple example illustrating the principle of automating this parameter estimation procedure. Further refinements to this approach would involve the estimation of how penetrable surface features were to flood flow.

Having separated the DSM into a ground DEM and an extracted surface feature layer, the potential for classifying this surface layer can be studied. The potential role of an ANN in the overall processing of LiDAR DSM data has been considered by Jaafar et al. (1999) but it is as a discriminator of features within the residual

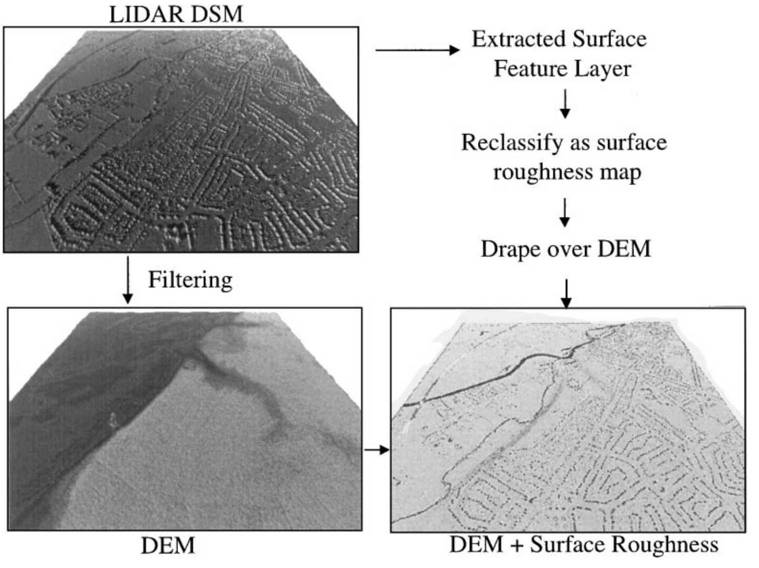

Fig. 8. The separation of the Digital Elevation Model (DEM) and surface roughness.

surface layer that it is thought to be most promising. The combination of the topographic characteristics of features with additional information such as the spectral characteristics is seen to offer a set of inputs which could discriminate, for example, between buildings and trees. The uncertainty over the importance of the various weightings to be attached to inputs suggests that an ANN could be a useful tool in classifying surface features and therefore refining estimates of surface roughness.

5. Further research

Early research in exploring the use of an ANN has utilised the Stuttgart Neural Network Simulation (SNNS) using a back propagation algorithm (Zell et al., 1994). The major task is to identify an appropriate set of inputs to the network that will discriminate between the classes (Evans, 1996; Kavzoglu & Mather, 1999; Mather, 1987). In this study, the classes to be differentiated are buildings, trees and the ground surface and the approach followed is that suggested by Hirose, Yamashita and Hijiya (1991). Initial trials using topographic indices alone such as the area, standard deviation of elevation, mean slope and maximum elevation for features within the residual surface proved unsuccessful. Additional information from the multi-spectral Compact Airborne Spectrographic Imager operated by the Environment Agency is being used to provide additional inputs to the classification process.

The forthcoming use of LiDAR sensors which detect a second laser return in addition to the initial laser return will allow the degree to which objects are penetrable to be represented. This should offer a useful additional input to the classification process which should distinguish between solid objects such as buildings and less dense objects such as trees, a characteristic which is directly applicable to the estimation of hydraulic roughness parameters for flood inundation studies.

So far the techniques considered have used only remotely sensed data sources. The availability of existing vector mapping would allow different strategies to be pursued. Large-scale vector building outlines could be used to classify one set of surface features leaving other features to be assigned a non-building class and therefore an appropriate roughness coefficient. Finally the need for direct accuracy assessment to validate DEM creation and surface feature classification is a vital component of the continuation of this research.

6. Conclusions

The nature of LiDAR data offers the potential for extracting surface information fit for many applications. The extraction of discrete features such as buildings for land use change and mapping purposes presents many research challenges. For many applications, however, relatively simple filtering procedures can provide information fit for their purpose. The case of flood inundation modelling illustrates how surface features typical of urban land uses occupying the floodplain can be separated from the ground surface. Further classification of this surface feature layer based upon a combination of topographic and spectral information using an ANN classifier offers the potential for refining surface roughness parameters for improved modelling of flood flow from rivers in semi-urban areas.

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