# GROUND SURFACE ESTIMATION FROM AIRBORNE LASER SCANNER DATA USING ACTIVE SHAPE MODELS

M. Elmqvist

Department of Laser Systems, Swedish Defence Research Agency,Linköping

## ABSTRACT

Various filtering techniques exist to obtain the ground from laser radar data to use when building digital terrain models. This paper develops an active shape model approach to estimate the ground surface from laser radar data. The active shape model acts like a rubber cloth with elasticity and rigidity. With constraint forces the model is formed to an estimate of the ground surface. The model is glued against the measured points from underneath, forming the envelope of the point cloud. Even in a thick forest as much as 25 per cent of the data points represent the ground. The stiffness of the shape model stretches it out to a continuous surface in between the ground points. The algorithm implemented in this paper is suited to use on very dense data sets, it has been designed for data sets of more than 10 points per square meter. We propose suggestions of changes to the algorithm to adjust it to work on more sparse data sets.

## 1. INTRODUCTION

At FOI at the Division of sensor technology there is a program for synthetic environments and sensor simulation (Ahlberg et al. 2001). The aim of the program is to develop methods for automatic construction of terrain models based on laser radar data. The cause is to meet the need for high resolution terrain data for mission planning, command and control and accurate sensor simulation in tactical simulations. Apart from the ground estimation algorithm developed in this paper, algorithms for single tree extraction (Persson, 2001) and algorithms for estimation of buildings have been developed within the program.

Both airborne laser radars and ground based laser radars are used for the data gathering. The data used as input for the ground estimation algorithm is from an airborne system provided by TopEye AB. The system contains a vertical scanning direct detection laser radar operating at a wavelength of 1.06um. The pulse rate is between 2 and 7 kHz and the emitted energy is about 0.1 mJ per pulse. The operational altitude is approximately 60-900m. The TopEye system is able to produce point position, intensity of reflection as well as multiple return or double echo data. The laser data used in our work was acquired at missions in 1998, 1999 and 2000. We required dense data sets and hence the missions were flown at slow speed, i.e. 10-25 m/s, and at rather low altitudes, 120-375m. Some areas were also flown in two directions perpendicular to each other. The resulting data sets have a density that varies between 2 - 16 points per square meter.

### 1.1 Related work

At the Institute of photogrammetry and remote sensing at Vienna University of technology, a method based on iterative linear prediction has been developed and tested (Pfeifer et al. 1998). The test has been performed on data from wooded areas. This method works by iteratively interpolating the ground surface. First, a rough surface approximation is computed using the same weight for all points. The obtained surface will run in an averaging way between ground points and non-ground points. Next residuals are computed for each point with respect to this surface. The majority of the ground points will get a negative residual, whereas the majority of non-ground points, e.g. vegetation, will get small negative or positive residuals. Finally, new weights are computed for each point using the residuals. To compute the new weights, a special adaptive weight function is used. In Figure 1 the principal form of this function is illustrated.
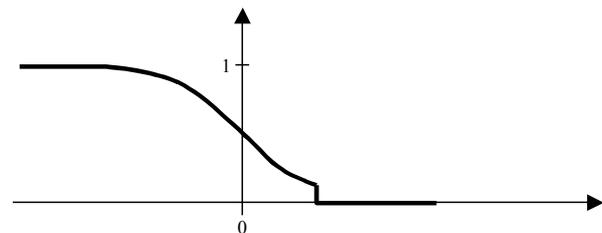


Figure 1. Weight function used to associate new weights to measured points using residuals. Points with large negative residuals get large weights and points with medium residuals will get smaller weights. Points with large positive residuals get no weight at all and hence become "eliminated"(Pfeifer et al. 1998).

In each of the succeeding iterations, a new surface is interpolated using the original points and the previously derived weights. In this way, the iterative surface interpolation will converge towards a final solution. Break lines, like cliffs or edges of an embankment, always become

blurred since the weighted interpolation works like a low pass filter.

At the Department of geodesy and photogrammetry at the Royal institute of technology, Stockholm, Sweden, another method for DTM construction has been developed (Axelsson, 1999). A commercial software implementation based on this work can be found in the TerraScan package (TerraScan, 1999). In his paper, Axelsson describes the method in one dimension. The method processes one swath at a time. He reports that work will proceed and a two-dimensional surface-based implementation based on a triangular irregular network (TIN) will be carried out. The basic idea is to start with a surface beneath all laser points, see Figure 2. This surface is then connected to the ground points from below using some sort of criteria. Axelsson enumerates a number of possible criteria for controlling the connection, e.g. Minimum Description Length (MDL), that he uses in his implementation. All criteria have in common that they delimit the possible shapes and hence fluctuations of the resulting surface in some way or another.
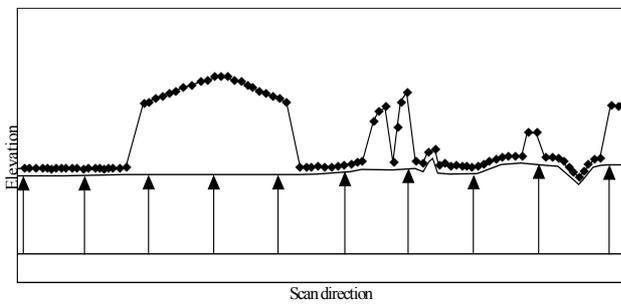


Figure 2. Connecting ground surface to points of one swath, (Axelsson, 1999).

The TerraScan implementation is based on this work. It is two-dimensional and surface-based and works as follows. First, a rectangular grid of which the size is controlled by user-supplied parameters is created and placed over the point cloud. For each mesh the lowest point is selected as a connection point, i.e. is classified as a ground point. The selected points are triangulated resulting in an initial TIN based surface representation of the ground surface. Besides the connection points this initial surface is entirely beneath the point cloud.

Another process now starts where the final surface is constructed by iteratively adding new points to this triangulation. One point at a time is selected from the point cloud and based on different criteria it is accepted or rejected as a new connection point. Each new connection point is inserted in the triangulation and makes the surface follow the ground more closely. User-supplied parameters are used in the criteria to control the selection. One criterion is based on the distance between a candidate point and the present surface. Another criterion, referred to as the iteration angel, is based on the angel between the surface with and without the candidate point. The connection points used in the resulting TIN surface constitute a subset of the actual measured points. Hence, for those connection points that really are ground points the accuracy of the approximation of the real ground surface is equal to the accuracy of the laser measurement system.

## 2. ACTIVE SHAPE MODELS

Active shape models are something in between the fields of image processing and computer graphics. A deformable model is influenced by an image to be transformed into a certain shape. In image processing the models are used to find edges and lines in images and referred to as active contours. Due to their nature the active contours are suited to find continuous edges or lines in the images.

When dealing with contours in two dimensional images the active contour is commonly mentioned as a snake (Kass et al,1988).

The shape of the active contour is the solution that minimizes an energy function. The energy function consists of material behavior like elasticity and rigidity of the snake. It is also a function of the attractor image derived from features in the image.

In this algorithm for ground estimation the active shape model can be liken with a sticky rubber cloth being pushed up from beneath. The cloth sticks to the lowest points, forming a continuous surface.

### 2.1 Theory

The model is a discrete two dimensional surface in a three dimensional environment. The surface position is given in a parametric form by $v[k] = (x(k), y(k), z(k))$ The shape of the model is controlled by an energy function. The shape of the model minimizes this energy function,

$$E(v) = \sum (E_{\text{int}}(v[k]) + E_{im}(v[k]) + E_{ext}(v[k])) \qquad (1)$$

$E_{\text{int}}$ is the internal energy of the model, it gives the surface its smoothness. The internal energy is derived from the elasticity and rigidity of the model i.e. a function of the first and second derivatives of the surface

$E_{im}$ is the potential field created from the laser radar image. If this function is the distance between the measured surface and the model, it gives a model that is attracted to the laser data points.

$E_{ext}$ is derived from other constraint forces guiding the model to a preferred shape.

The minimization of the energy function is an iterative process and the model is given start values near the wanted solution. Start values are often a local minimum of the energy function $E$. Using different start values will in most cases result in models of different shapes after the minimization. This is not a problem in this case when using the models to estimate the ground surface from laser radar data, since there are no measured points below the ground the model can safely be started from below.

## 3. IMPLEMENTATION

In the implementation of this algorithm at FOI, some simplifications have been done due to the appearance of the

laser radar data used. The intent is to speed up the algorithm and reduce the size of memory needed.

Since the data is very dense, more than 10 points per square meter, the data set is re sampled into a regular grid. This is not such a good idea when dealing with more sparse data sets. The re sampling of the data is done in the simplest way possible, using the lowest point in each mesh. This is preferable instead of make any interpolation between near points. In a forest area a single grid mesh often contains both measurements belonging to the trees and to the ground, in such a case it is better to use the lowest measured point rather than some mean between the ground and the tree points. Grid points with no data are left blank, no interpolation is done between neighbour points.

From this re sampling of the data a two dimensional height image is received, $I(x, y)$. The active shape model is represented by a height matrix, $v(x, y)$, with the same size as $I$.

$E_{int}$ from (1) adds stiffness to the model. In this implementation $E_{int}$ is a function of the first derivative of the model, giving it elasticity but not rigidity. The result is a model able to form sharp edges, from this the model is more to be liken with a net of rubber bands rather than splines. Wanting the model to bend down steep slopes but still stretch out flat under buildings and other objects, the function $E_{int}$ is non linear.

$$E_{int}(x, y) = C \sum_{m=x-1}^{x+1} \sum_{n=y-1}^{y+1} \left| \arctan(v(x, y) - v(m, n)) \right| \qquad (2)$$

This has of course its minimum when the model forms a plane where $v(x, y) \equiv v$. $C$ is the elasticity constant and define how hard the model is to form. By adjusting this constant $C$ it is possible to control how rough the model will turn out.

$E_{im}$ from (1) is a function of the distance between $I$ and $v$.

$$E_{im}(x, y) = -Ae^{-a(I(x,y) - v(x,y))^2} \qquad (3)$$

This function makes the model attach to $I$, having the minimum energy when $v=I$. The constants $A$ and $a$ controls the attraction strength and attraction length of the model. This function attract the model with a strong force but on a short range, i.e. either the model is unaffected by $I$ in a point or $v$ is glued to it. In Figure 3 the principle of the behaviour of the model due to this is shown. The strong attraction force makes the model attach to the ground points once the model is close enough. Points belonging to measurements in the tree, leave the model unaffected. The internal elasticity of the model produces forces too weak to pull the model away from already attached nodes but are strong enough to stretch the surface where it is not influenced of the image attraction.
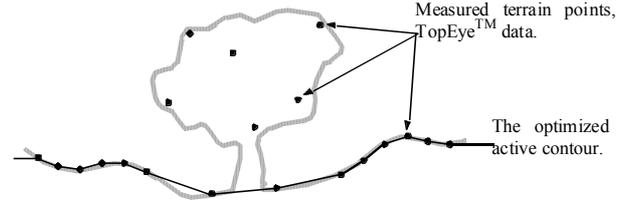


Figure 3. A section of the model. The measured points from the tree is too far from the model to attract it, the elasticity of the model streches it between the ground points.

The minimization of (1) is done in an iterative process where $E(v)$ decreases by updating the nodes of the model surface in small steps until a local minimum is found. In each node of the model the new Z value that minimizes the energy function is calculated. When the model then is updated, these values no longer minimize the energy function because the value of the energy function in a point is dependent on the neighbour nodes. In the next iterations new Z values are calculated until the process converge towards the final solution. To speed up this process, the iterations are stopped when the maximum step size of the model is less than 5 cm.

The start value of $v$ is a plane under the lowest point in $I$. To speed up the algorithm, an external component of the energy function is added initially

$$E_{ext}(x, y) = -Gv(x, y) \qquad (4)$$

This rises the model guiding it close towards the ground enough to let the function $E_{im}$ attract the model. When a local minimum of the energy function is found, $E_{ext}$ causes the model to bubble up in areas where the model has not been attracted to the height image. This is obvious under large objects, as buildings, where the model is forming a cushion instead of being stretched out. The simple solution of this problem is to turn the external component off and run the algorithm again. This only takes a few iterations since the model now is close to the solution of (1).

## 4. PERFORMANCE OF THE ALGORITHM

The algorithm has proven itself to be very robust, working on data sets of different types of terrain. It has been run on city areas, areas with different types of vegetation and in rough and flat areas. This has been done with the same settings of the control parameters.

In Figure 4 the effect of the non linear elasticity function is shown. The elasticity function gets saturated and the model is able to bend down the slope. In Figure 5 another test image is shown, this is processed with the same parameter settings of the algorithm. This time the model is too stiff to climb up to the roof of the buildings. What really differ this image from the one with the hill is that the hill is easy to climb from the left side. The attraction force is strong within a short range, the roof in Figure 5 is out of range, if on the other hand one side of the roof had reached the ground, the algorithm would have estimated it as ground.
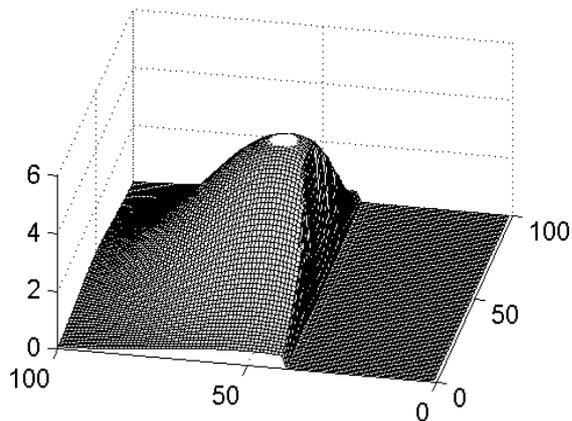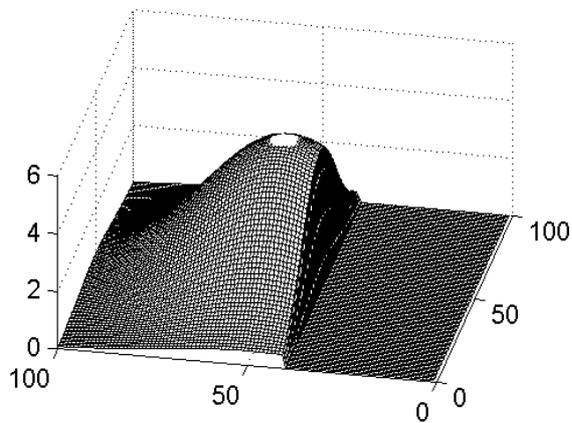




Figure 4. Top: A synthetic ground image, a cut off Gauss function, representing a hill with a steep slope. Bottom: The active shape model estimating the ground.
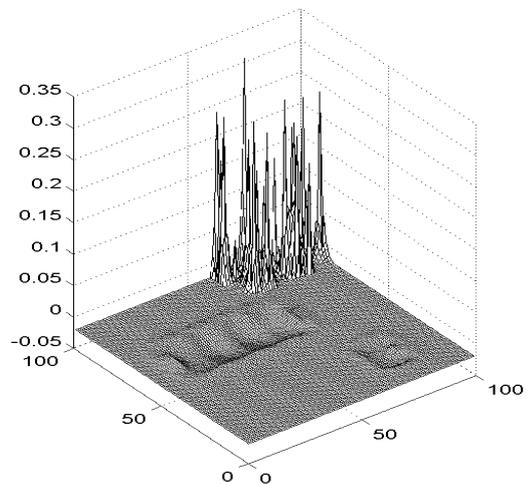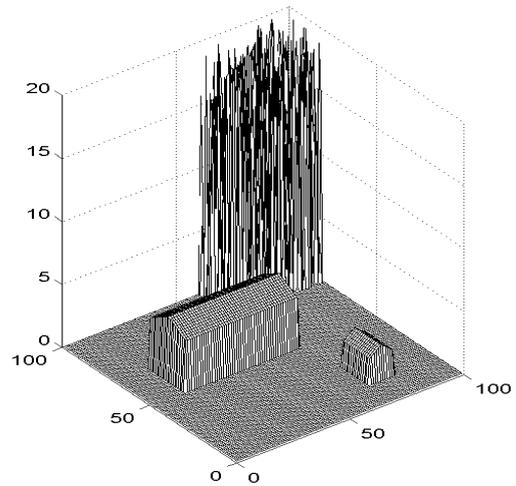




Figure 5. Top: A test image with two buildings and a forest block. The forest contains 25 per cent ground points and the tree points is spread between 0 and 20 m with uniform distribution Bottom: The estimated ground. Note the scaling of the axis!

One example from a real scene is illustrated in Figure 6 and Figure 7. The image covers an area of 100x100 m, containing a road with an underpass and a hill with small trees. The distortions on the road comes from street lamps and passing cars.
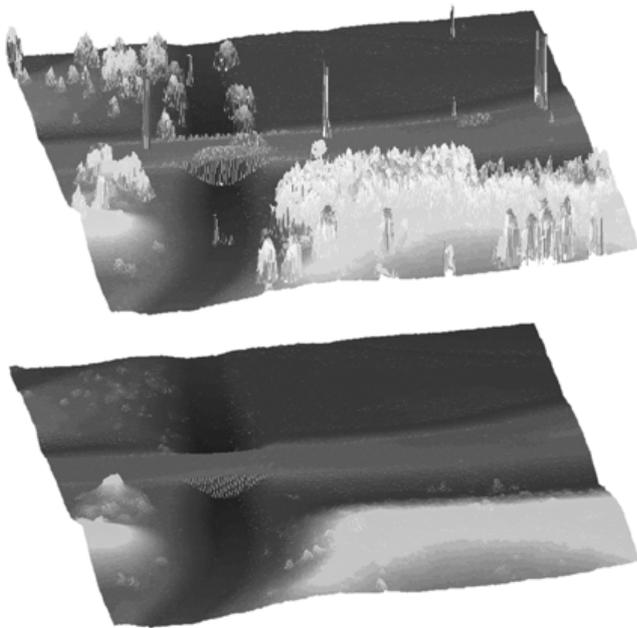
Figure 6 A test area including a road, street lamps, an underpass and a small vegetation area with small pine trees. Top: raw laser data. Bottom: the estimated ground surface
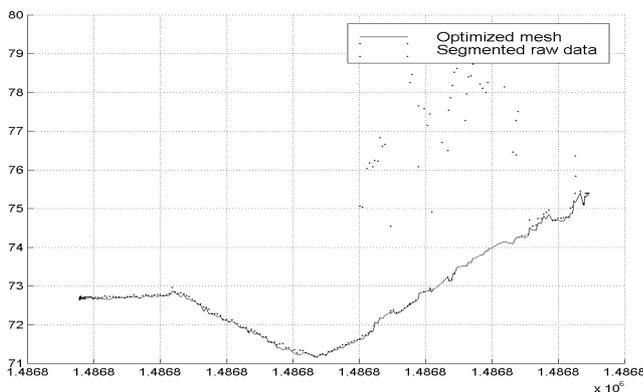


Figure 7 Estimated ground surface for a single laser radar swath. From left: the road, a ditch and a slope with trees.

## 5. DISCUSSION

When the surface estimation is done it is possible to add a classification step. By comparing the raw data set with the model, the points close enough to this surface are labeled as ground points, Figure 8. Then by picking out the ground points from the data set, a TIN is built using the original values from the data set.

When running the algorithm on more sparse data sets some problems occur due to the re sampling of the data into a regular grid. When the re sampling is done the true X,Y-values of the points are lost. The height value of the point is moved to the centre of the nearest mesh and it is not good if this is outside the original footprint of the laser. On the other hand, if the data is re sampled into a fine grid most of
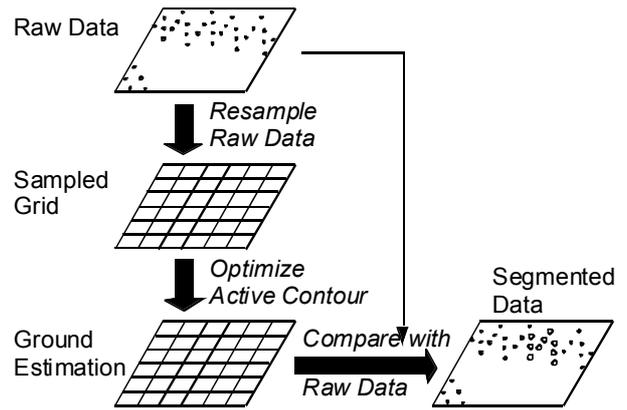


Figure 8.The classification chain of the laser scanner data

the grid points lack data, this makes the algorithm slow. It is preferred that the grid points are approximately of the same number as the raw data points. In the data sets the algorithm was designed for, the laser footprint is about 0.3-0.5 m. The grid size has been set to 0.25 m. This gives a maximum error of displacement in X,Y of a laser point to less than 18 cm.

One way to handle the displacement of points would be to adjust the algorithm to work with a TIN model instead of a mesh. The most straight forward method would be to let the model have the same number of vertices as the number of laser data points. A better way is probably to let the model have a variable number of control points, adding vertices near edges.

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