DETERMINATION OF TERRAIN MODELS BY DIGITAL IMAGE MATCHING METHODS

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ABSTRACT:

Today, digital terrain models (DTMs) are used in many fields of science and practice. When modelling the earth's surface it is necessary to make a clear distinction between terrain models, i.e. models representing the terrain in the sense of the 'bare soil', and surface models, i.e. models that also include artificial buildings and vegetation. A DTM should not be influenced by off-terrain points such as points on vegetation and on buildings. Hierarchical robust filtering, a method for eliminating the influence of the off-terrain-points in DTM generation, has been shown to give good results for airborne laser-scanner-data. In this paper, we want to show that this method can also be applied successfully to improve the quality of DTMs created by image matching techniques. Those techniques deliver a digital surface model containing disturbances such as houses and forests, even if filtering methods are an integral part of the matching process. Hierarchical robust filtering, implemented in the program package SCOP++, can be used in order to eliminate these errors in the DTM. The results presented in this paper show the improvement of DTMs created by matching methods that can be achieved by this method, using test data from different areas of interest.

1. INTRODUCTION

Digital terrain models (DTMs) are important components in Geographic Information Systems, and they are used in many fields of science and practice. There are different ways of representing a DTM in the computer. Often the terrain is represented by heights in a regular grid. For a high-quality description of the terrain, a hybrid raster can be used, containing not only the grid heights, but also geomorphologic elements such as break lines or spot heights. The elevations of the grid points are not measured directly, but they have to be determined from irregularly distributed points and the geomorphologic elements, e.g. by linear prediction, or by interpolation based on finite elements (Kraus, 2000). The original points can be acquired in different ways. Traditionally, they were measured manually in stereoscopic images. Image matching methods have been successfully applied to automate DTM generation from digital aerial images (Gülch, 1994; Krzystek, 1995), which has resulted in operational software modules such as MATCH-T by INPHO GmbH (INPHO, 2003) that are widely-used today. In addition to photogrammetric techniques, the original data for DTM generation can also be acquired by airborne laser scanning (ALS) (Kraus, 2000).

It is common to both image matching techniques and ALS that the original point cloud represents the earth's surface as it is seen from the sensor's vantage point. The original point cloud does not only consist of points located on the terrain, but it also contains off-terrain points on houses, trees, or other objects. Thus, a model interpolated from that point cloud is a digital surface model (DSM) rather than a DTM. For applications such as orthophoto production, a DSM might be sufficient. For other applications it is essential to eliminate the off-terrain points to obtain a model that really represents the terrain. In image matching, robust interpolation techniques are used to eliminate these off-terrain points (Krzystek, 1995), but problems arise in densely built-up regions and in forests, and manual intervention is often required to remove remaining errors.

With respect to ALS data, *hierarchical robust linear prediction* has been shown to give excellent results in densely built-up and forested areas (Kraus and Pfeifer, 1998; Briese et al., 2002). It is the goal of this paper to show how this method can be applied to improve DTMs derived by image matching. We start with a description of the characteristics of DSMs derived from image matching and with an outline of the filter algorithm. After that, we show how the filter algorithm is adapted to the specific characteristics of point clouds derived by image matching. Finally, we will present results achieved for various types of terrain and land cover.

2. DTM GENERATION USING IMAGE MATCHING

In this work, we used the program MATCH-T from INPHO GmbH (INPHO, 2003) for the generation of a DSM from aerial images. MATCH-T applies feature based matching to generate a dense point cloud. From this point cloud, an elevation grid is interpolated by the finite element method, applying robust estimation to eliminate false matches (Krzystek, 1995). The major goal of this work was to create a DTM without buildings and vegetation. MATCH-T has various parameters which control the point density in the matching process and the degree of smoothing during the grid interpolation. By these parameters, the user can control the degree to which the resulting elevation grid represents the terrain (Summit Evolution, 2001):

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- The *grid width* of the resulting elevation grid is a fundamental parameter that is in general selected according to the application-specific requirements for the DTM, within certain limits given by the scale of the aerial images used for matching. Selecting a larger grid size yields a smoothing effect that helps to eliminate off-terrain points, but also smoothes terrain structures that one might want to preserve.
- The *terrain type* (flat, undulating, mountainous) has to be selected in accordance with the actual terrain type to make matching successful.
- The *degree of smoothing* (high, medium, low) is the parameter that is best suited for controlling whether to obtain a DTM or a DSM. In this work, we selected the degree of smoothing to be “high”, to obtain an initial elevation grid as close as possible to the terrain.
- The *density of the original point cloud* (dense, medium, sparse) also influences the degree of smoothing: a sparse point cloud results in a model closer to the terrain than a dense point cloud.
- MATCH-T can consider geomorphologic elements and additional points in the interpolation process, typically measured interactively by a human operator. The *standard deviation of surface points and break lines* has an influence on the weights of these additional observations in the interpolation process.

MATCH-T delivers DSMs of good quality. If a DTM is required, the algorithms for smoothing work well if the grid width is not too small compared to the extents of groups of off-terrain points in the original point cloud. For instance, groups of trees and single buildings can be eliminated if the grid width is in the range of about 5-10 m. However, if the grid width is chosen smaller, e.g. 1.5 m, these objects remain in the matching results, even if a high degree of smoothing is selected. Figure 1 shows a DSM generated by image matching with a resolution of 1.25 m. The remaining buildings are clearly visible.

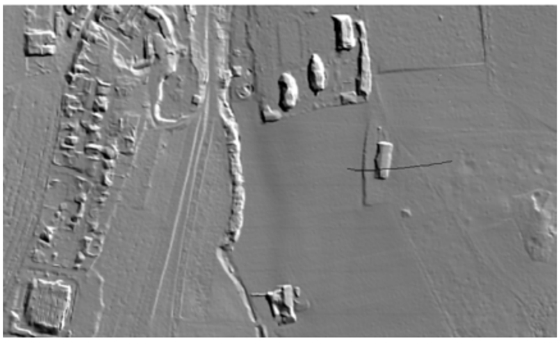

Figure 1. Shaded view of an elevation grid acquired by image matching (Eggenburg east; cf. section 5).

As in general the grid width has to be chosen in dependence of the proposed application of a DTM, there is only a small band width for adapting this parameter. That is why we propose to improve the image matching results by hierarchical robust linear prediction in a post-processing step. Our good experience with that technique gives us reason to believe that it should be possible to eliminate buildings and groups of trees in high-density DSMs delivered by image matching techniques.

3. HIERARCHICAL ROBUST LINEAR PREDICTION

We use the program SCOP++ (Briese et al., 2002) for the interpolation of a hybrid raster DTM on the basis of irregular point and vector data by linear prediction. This method is based on the assumption that the heights of terrain points, after removing a trend, are correlated, the correlation being a function of the horizontal distance between the points (Kraus, 2000). Linear prediction will be fragile if gross errors occur, so that a more robust approach has to be found. In this section, we want to describe how this can be accomplished.

3.1 Robust Interpolation

Robust interpolation (Kraus and Pfeifer, 1998) was developed for DTM generation from ALS-data in wooded areas. In this process the elimination of gross errors and the interpolation of the terrain are carried out simultaneously. This process consists of three steps:

1. Interpolation of a surface model by linear prediction considering individual weights for each point. At the beginning all weights are assumed to be equal.
2. Calculation of the filter values, i.e., the vertical distances from the interpolated surface to the measured points
3. Recomputation of the weights of the individual points in dependence of the filter values, using a weight function adapted to the stochastic properties of the filter values of the off-terrain points.

The steps are repeated in an iterative process until all gross errors are eliminated. The elimination of gross errors (off-terrain points) is controlled by the weight function. This weight function is controlled by 3 parameters (figure 2): *Halfweight h* (the size of a filter value obtaining a weight of 0.5), *slant s* (co-tangent of the slope at $f=h$), and the *cut-off point t*.

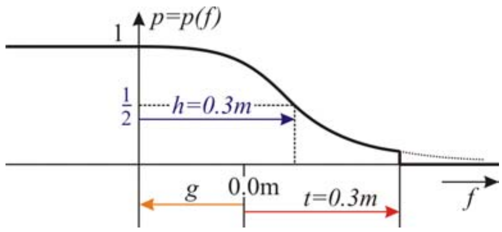

Figure 2. Weight function (Briese et al., 2002).

The values for *h*, *s*, and *t* can be set independently for the positive and the negative branches of the weight function, i.e. for points above and below the surface interpolated in the previous iteration. As a consequence, the weight function can be asymmetric. This allows to favour points on or below the intermediate surface (considered to be terrain points) and to decrease the weights of points above the intermediate surface that are more likely to be off-terrain points. The function is also shifted by a value *g*. This also should compensate for the fact that the intermediate surface is more likely to be above the terrain than below it. By choosing the weight function to be asymmetric and excentric, we model the actual distribution of the errors of the off-terrain points with respect to the terrain. Figure 2 shows a weight function for the elimination of off-terrain points; note that in this case, points having a filter value $f < g$ are not affected by robust estimation (Briese et al., 2002).

3.2 Hierarchical Robust Interpolation

Robust interpolation relies on a ‘good mixture’ of terrain and off-terrain points, but the algorithm is not able to eliminate clusters of off-terrain points as they occur, e.g., in densely developed urban areas. To meet this problem, robust interpolation is applied in a hierarchical framework. The main feature of the *hierarchical robust interpolation* is the creation of a data pyramid representing the data at different resolution levels. Robust interpolation is applied to thinned-out data first, the interpolation results being used to eliminate off-terrain points for the next iteration that is carried out using the data of the next finer resolution of the data pyramid. Three steps are carried out at each level of the data pyramid:

1. Thin out the original data according to the resolution of the current level of the data pyramid, using only points not yet classified as being off-terrain points
2. Generate a DTM by robust interpolation, using the thinned-out data
3. Compare the DTM thus generated with the original data. Data points outside a certain tolerance band are classified to be off-terrain points and, thus, no longer considered in the subsequent iterations.

At the finest level, the DTM is computed from all original points classified as terrain points. Using this method, the generation of DTM from ALS data in densely built-up areas has been shown to be feasible (Briese, et al., 2002). Using thinned-out data, the influence of large clusters of off-terrain points (e.g. points on buildings) can be eliminated but the resulting DTM also has a rather coarse resolution. The influence of low vegetation (e.g. bushes) is eliminated using the data at a finer resolution, a process that also results in a better DTM.

4. HIERARCHICAL ROBUST INTERPOLATION FOR DTMS FROM IMAGE MATCHING

As mentioned above, hierarchical robust filtering was primarily created for DTM generation from ALS data. However, in this paper the original point cloud is a grid that was generated by an interpolation with finite elements from the initial results of feature based matching by MATCH-T.

4.1 Characteristics of the data

Figure 3 shows the different characteristics of point clouds from image matching and ALS. The dots represent the grid points derived by image matching with a low degree of smoothing in grid interpolation. The red line shows the DSM that can be generated from these grid points. The crosses represent the ALS points. The green dotted line represents the DSM obtained from ALS data. One essential difference between point clouds from ALS and image matching is that image matching does not deliver terrain points in wooded areas because corresponding points are only determined on the tops of the tree canopies. On the other hand, ALS does provide a point cloud with a good mixture of terrain and off-terrain points, because the laser beam can at least partly penetrate tree canopies. If there is no 'good mixture' of terrain and off-terrain-points, robust filtering will not be able to eliminate gross errors. As a consequence, off-terrain points from a point cloud derived by image matching cannot be expected to be eliminated in forests. The second big difference between point clouds from ALS and point clouds from image matching is that, unlike ALS data, point grids from image matching are pre- filtered in the matching process. The effect is that the outlines of buildings and other objects are blurred, which in densely built-up areas might result in narrow inner courtyards without points on the terrain. Consequently, the areas without actual terrain points might be larger for point clouds image matching than for ALS data. This has to be considered when applying hierarchical robust filtering to point clouds derived from image matching.

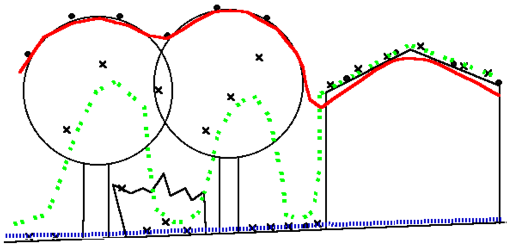

Figure 3. Different characteristics of point clouds from image matching (dots) and ALS (crosses) and the resulting DSMs; DTM = blue dotted line.

4.2 Adaptation of the filter strategy

The strategy applied in this work is based on a strategy that has been shown to give good results in DTM generation from ALS data in low-density areas (figure 4).

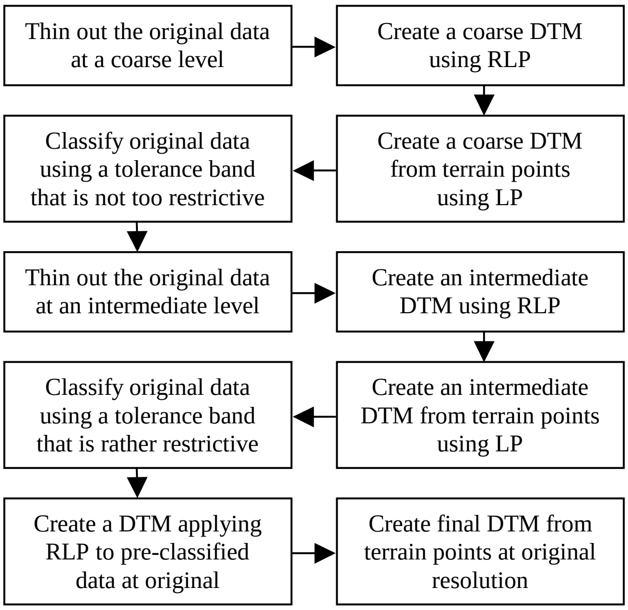

Figure 4. Work flow for our filter strategy. LP: Linear Prediction, RLP: Robust Linear Prediction.

The terrain type, the density of vegetation and development, and the average building dimensions are the determining factors for an adequate filtering strategy. It turned out to be necessary to have three iterations of the loop of thinning out, filtering, and eliminating points off the intermediate DTM, described in section 3.2. In each loop, the parameters were set in a way to take into account the peculiarities of the matched points.

4.2.1 Generation of a Coarse DTM by Rigorous Thinning and Filtering: In this first step, a DTM is created from data that are rigorously thinned out by selecting the lowest point within a certain neighbourhood. The degree to which the data are thinned out, controlled by selecting the grid width of the thinned-out data, is of crucial importance to the success of the whole procedure. It must not be chosen too small, because otherwise objects such as buildings and groups of trees cannot be eliminated. On the other hand, it must not be chosen too large, because this would result in too high a degree of smoothing of relevant terrain structures, especially in undulated terrain. For reasons described in section 4.1, the degree of thinning has to be higher with point clouds from image matching than for ALS data. We chose the grid width for thinning out to be about half the linear extent of the largest object we wanted to eliminate, e.g. 30 m in a data set containing areas without terrain points with an extent of 60 x 60 m^2. As a consequence, the terrain cannot be modelled very accurately in densely built-up areas for lack of terrain points within narrow gaps between the individual buildings, and because a higher degree of smoothing is required to eliminate the buildings.

Having thinned out the data, robust interpolation is applied to eliminate off-terrain points. Selecting the filter parameters in this first iteration is crucial for the success of the overall process: larger objects not eliminated at this stage will remain in the DTM until the end, whereas larger terrain features that are cut-off cannot be regained in the subsequent iterations. It turned out to be good practice to eliminate only points on the positive branch of the weight function. For points below the initial estimate of the surface, the weights remained unchanged. This implies that outliers underneath the terrain are not eliminated at this stage. Several iterations were carried out with a weight function that was not too restrictive in order not to eliminate too many terrain points ($h = 0.4\ m$). The cut-off point t was chosen to be 1.5 m. All points being more than 1.5 m above the DTM in the last iteration were classified as off-terrain points. To get an optimal estimate of the DTM representing the terrain after the first iteration of filtering, linear prediction using the original weights was carried out, considering only points classified to be on the terrain. The grid width of this DTM was set to a value smaller than the thinning parameter, e.g. 5 m in our examples (with a grid width of the original data of 1.25 m). At this stage, the influence of off-terrain points has not yet been completely eliminated, and the terrain is still modelled very coarsely.

4.2.2 Intermediate Filtering to Improve the Coarse DTM: This second iteration starts with a classification of the original point cloud with respect to the DTM generated in the first iteration. Points within a certain tolerance band around the DTM are classified as potential terrain points and thus accepted for further computation. All the other points are eliminated. The width of the tolerance band has to be selected carefully in order to include as many actual terrain points as possible, while still eliminating a considerable portion of the off-terrain points. We selected a band with a bias towards points below the terrain, accepting points as far as 3 m below the initial DTM (to eliminate large negative outliers delivered more frequently by image matching methods than by ALS), but only 2 m above it. Using a more restrictive upper threshold than 2 m would have resulted in too great a number of terrain points to be eliminated. The DTM from iteration 1 is too coarse to perform such a rigorous step already at this stage of processing. Consequently, off-terrain points at building outlines and on the tops of small trees are still included in the data. These points are to be eliminated in the second processing stage.

The original points classified as terrain points are thinned out again, using a smaller thinning parameter than in the first iteration (here: by selecting the lowest point within a regular grid width of 3 m). Robust linear prediction is applied to the thinned out data once again, but using more rigorous parameter settings for the weight functions in order to eliminate the influence of off-terrain points at the building outlines and on low vegetation ($h = 0.3\ m$). Unlike in the first iteration, robust estimation was also applied to points below the terrain to take into consideration the more frequent occurrence of 'negative' errors in image matching results compared to ALS. Again, several iterations of robust estimation were carried out, using a cut-off point $t = 0.3\ m$. All points having a filter value between -0.3 m and +0.3 m in the last iteration are considered to be terrain points. These points are used to compute the second approximation of the DTM by linear prediction, using the original weights. This DTM, interpolated with a grid width of 2 m in most of our examples, is supposed to be already quite a good approximation of the terrain, though it still contains few off-terrain points on low vegetation.

4.2.3 Final DTM Generation: The DTM created in iteration 2 is again used to classify the original points, this time using a more restrictive tolerance band (e.g. eliminating points more than 2 m below or more than 1 m above the intermediate DTM), because the approximation is a much better one than in the previous iteration. Robust linear prediction using very restrictive values ($h = s = t = 0.15\ m$) is applied to remove the remaining off-terrain points. In this final stage, robust estimation is again only applied to points above the intermediate DTM. This means that at this stage we assume that all large 'negative' outliers have already been eliminated in the previous filtering loop. The final DTM is created from the points classified as terrain points in the final iteration of robust estimation by linear prediction using the original weights. The grid width of the final DTM has to be selected in accordance with the resolution of the original point cloud.

5. RESULTS

In order to test our filter algorithm, three data sets of quite different characteristics with respect to land cover and image geometry were used.

5.1 The Test Data

The first data set, captured over Eggenburg (Lower Austria) consisted of high-resolution aerial images of a historic town and its surroundings and was characterised by undulating terrain with both densely-built up areas in the town centre and forested and agricultural regions with little but dense vegetation at the fringes. The second data set consisted of high-resolution images of a waste disposal site in Stockerau (Lower Austria), including few buildings and man-made "terrain" shapes. The third data set was captured over the Schneealm mountain range in Styria, characterized by rugged terrain and partly by dense forest. For all test sites, a DSM was derived using MATCH-T, selecting a high degree of smoothing. Table 1 gives an overview of the flight parameters and the parameter settings for MATCH-T. The grid points derived by MATCH-T provided the input for our filter algorithm.

Area	S = 1:	f [mm]	r [µm]	terrain type	Point density	Δ [m]
Eggenburg	4500	152	30	U	M	1.25
Stockerau	3500	208	30	U	D	1.25
Schneealm	15000	214	30	M	D	10.00

Table 1. Image scales S, focal lengths f, and scanning resolution r of the aerial images for the three test sites. Terrain type (U: undulating, M: mountainous), point density (M: medium, D: dense), and Δ (grid width) are the respective parameters for MATCH-T.

5.2 Results

We start this section with examples where the method was able to generate a DTM of good quality. The first examples are taken from the Eggenburg data set. Figure 1 shows a shading of a DSM acquired by image matching with MATCH-T before filtering with SCOP++ in an area in the east of Eggenburg. Figure 5 shows the DTM that could be derived by hierarchical robust filtering.

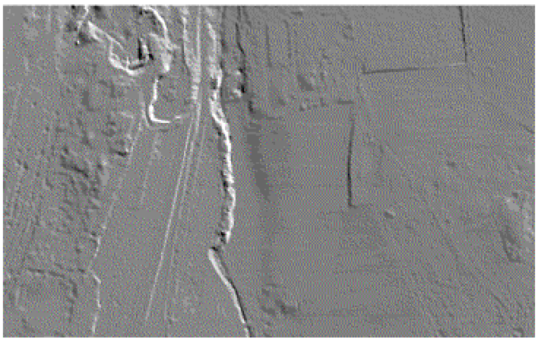

Figure 5. Shaded view of a DTM after including break lines and filtering with SCOP++ (Eggenburg east). The DSM is shown in figure 1.

The influence of the off-terrain points on houses could be eliminated completely. Even large buildings such as a factory in the left lower part and blocks of houses in the right upper part of the test area could be eliminated successfully. This was mainly achieved by choosing a rather coarse resolution of 15 m for thinning out the data in the first iteration, at the cost of a degree of smoothing that cut off some terrain features. If these smoothing effects are too large to be tolerated for the application of the DTM, break lines determined by interactive measurement can be considered in the filtering process. Thus, these smoothing effects can be avoided.

It was interesting to observe that using a high degree of smoothing in image matching smoothed the DSM at houses and trees without completely eliminating them. As a result, some off-terrain points were classified as terrain points by robust filtering because houses were not accentuated enough to be distinguished from the terrain. We think that it would be easier to select the appropriate parameters in each step of our filter strategy if the smoothing parameter were set to ‘low’ in image matching. Actually, it would be desirable not to filter or smooth the original data at all, to achieve a point distribution closer to the one delivered by ALS.

Figure 6 shows the result for another area in Eggenburg. The terrain is more undulating than in the example in figure 5, with some abrupt changes along a railway line and dense vegetation in the left lower part of the scene. Off-terrain points on houses could be eliminated again, but hierarchical robust filtering could not remove the off-terrain points in the dense forest south of the railway line. As predicted in section 4.1, this was caused by the lack of terrain points delivered by image matching. This problem could only be circumvented by manual measurement of 3D points on the terrain in the forest, which is, however, hardly feasible.

We selected the town centre of Eggenburg to check the performance of our method in a densely built-up area (figure 7). In the densely built-up area in the left lower part of the scene only a few terrain points were delivered by MATCH-T. The grid width for the first thinning of the data had to be chosen rather wide (30 m) in order to cope with large areas without any terrain points. Still, it was not possible to get as good a DTM as in the more rural areas of the previous examples. The reason for this is the lack of terrain points in inner courtyards and narrow streets between the houses. However, the influence of the off-terrain points on the houses could be eliminated and a DTM of quite a good quality could be achieved. Again, unwanted smoothing effects could be reduced by introducing break lines.

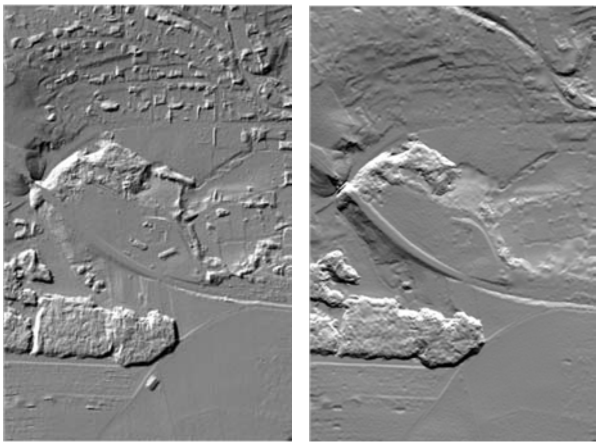

Figure 6. Shaded view of a DSM from image matching (left) and the resulting DTM after including break lines and filtering (right) (Eggenburg west).

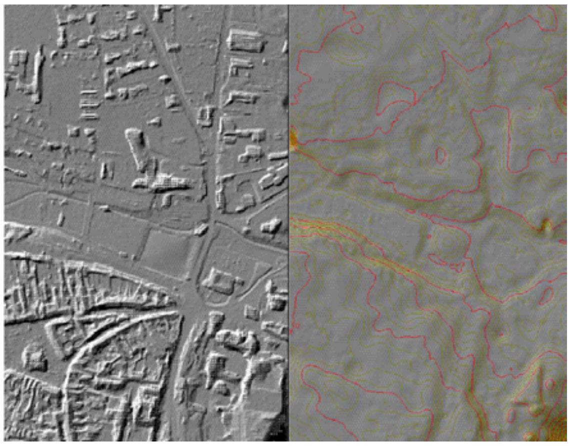

Figure 7. Shaded views of an elevation grid acquired by MATCH-T (left) and of a DTM after filtering (right) for the city centre of Eggenburg; contour lines in the DTM are shown.

Finally, we want to present some examples where our method failed to eliminate the influence of the off-terrain points. In the example taken from the waste disposal site near Stockerau, the influence of off-terrain points on buildings and vehicles should have been eliminated. The terrain contained small features such as heaps of sand and waste (figure 8). As the shapes and dimensions of the buildings are nearly the same as those of the terrain, no satisfying result could be achieved. The filtering method either eliminated both the buildings and heaps of sand and waste material, or it eliminated neither of them. It is, however, no surprise that the method only works if there is a distinction in appearance between the terrain and the objects that should be eliminated.

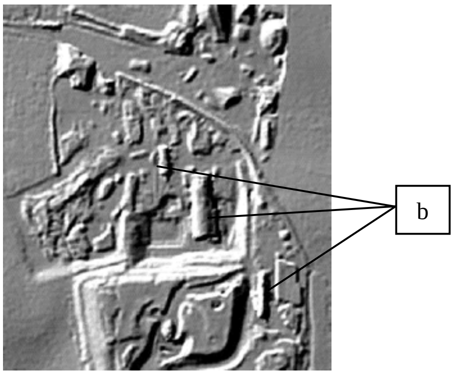

Figure 8. Shaded view of a DTM after filtering (Stockerau); b: buildings that could not be eliminated.

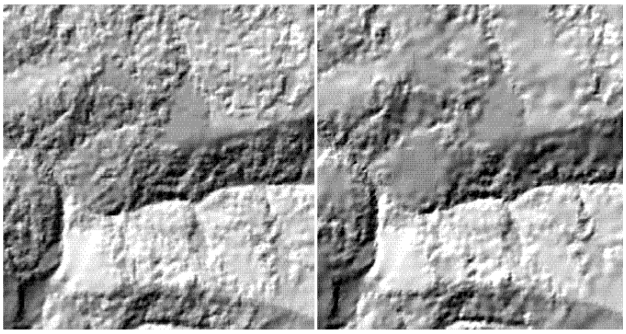

Figure 9. Shaded view of a DSM before (left) and after filtering (right) from the Scheealm test site.

The Schneealm test site was selected to find out whether our filtering method could be used to derive a good DTM in wooded areas. Given the image scale of that test site, the width of the elevation grid delivered by MATCH-T was chosen to be 10 m. Consequently, the parameters had to be set in a different way than described in section 4.2, even more so because only very few terrain points could be expected (e.g. in glades). The grid width for the first thinning-out was chosen to be 100 m. The parameters for the weight function had to be chosen rather restrictive in order to eliminate as many off-terrain points as possible ($h = s = t = 0.3\ m$). The terrain was modelled very coarsely after the first loop of thinning out and filtering the data, represented by a DTM with a grid width of 50 m. In the second iteration, the tolerance band was selected so that only points above the initial DTM were eliminated, whereas all points below that DTM were regarded to be terrain points. The original points classified as terrain points were thinned out using the lowest point within a grid with a width of 30 m. Robust linear prediction was applied using very restrictive parameters on the positive branch of the weight function ($h = s = t = 0.25m$), again in order to only eliminate points above the terrain. However, the method failed to eliminate the off-terrain points at this stage, so that the resulting intermediate surface model was not close enough to the terrain. Consequently, the third iteration could not succeed, either. Our filtering method could not deliver acceptable results because too few terrain points were provided by image matching, so the algorithm was not able to eliminate the influence of the off-terrain points on the trees (figure 9). The drawback of digital image matching methods compared to ALS in wooded areas was obvious.

6. SUMMARY AND OUTLOOK

A classification of the original point clouds into terrain points and off-terrain points is necessary in order to create a DTM from ALS data or image matching. We have shown how a method originally designed for the filtering of ALS data can be adapted to generate a DTM from the DSM created by image matching techniques. The basic difference between ALS point clouds and the image matching results is the distribution of the points in wooded and densely developed urban areas. The sequence of the applied strategy in SCOP++ might be the same for both data sets, but the parameters have to be adapted to the characteristics of DSMs from image matching. A point grid obtained from image matching techniques does still contain off-terrain points in spite of the filter methods integrated in the matching process. The method described in this work could be used to eliminate these errors concerning the DTM. Tests show that our method gives acceptable results for urban areas. The influence of off-terrain-points is widely eliminated, even though at the cost of some smoothing. However, these smoothing effects can be eliminated by the inclusion of break lines, so that a very good representation of the terrain can be achieved. The results for wooded areas are not satisfying because no terrain points are acquired by matching techniques. ALS data are much better suited for DTM generation in forested areas (Kraus and Pfeifer, 1998). A further improvement of the results is expected when using the unfiltered original data from the matching process or if the degree of smoothing in the matching process is selected to be as low as possible in order to eliminate undesirable pre-processing effects.

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