A ROBUST AUTOMATIC DIGITAL TERRAIN MODELLING METHOD BASED ON FUZZY LOGIC

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ABSTRACT

Most of the proposed methods for automatic DTM reconstruction are based on parametric estimation processes with very little capabilities for reasoning and decision making. Human operators which measure DTMs solve interpretation related problems while they carry out the geometric measurements. When working with terrain often decisions have to be made which are of imprecise nature. For those problems fuzzy logic is a perfect basis to design a fuzzy inference process.

In this paper we start to develop a fuzzy system for DTM acquisition. Fuzzy logic can be blended with proven concepts and modules of DTM generation and therefore may supplement rather than substitute classical procedures for DTM reconstruction. In a first step we design and implement algorithms for fuzzy feature detection and fuzzy matching in image space. The transfer from image space to object space is then carried out by classical spatial intersection combined with robust finite element modelling for the reconstruction of the terrain surface. Experiments with a Iranian test site are carried out and show the applicability of the procedure. In the next step of future work imprecise hypothetical information extracted from image space will be combined in a fuzzy manner with surface modelling to complete the fuzzy inference system.

1 INTRODUCTION

It is more than ten years ago that success in image matching has initiated the development of numerous concepts and routines for automatic acquisition of Digital Terrain Models (DTMs). First experiments with those routines have indicated that the automatic procedures promise high accuracy of the reconstructed surface. Today, DTM modules are mostly included in the software packages of digital photogrammetric systems and are widely applied in production. By listening to critical voices it has to be noticed that neither commercial nor academic DTM modules are doing the job in such a way that production highly benefits from automatically acquired DTMs. Many reports state that there is a fairly high demand for interactive DTM editing and post processing in standard applications.

A closer look to these methods shows that in general DTM collection procedures are based on parametric estimation processes combined with some robustification to eliminate errors. Obviously this classical concepts can not solve DTM data collection properly. There is, for example, no procedure in such processes which may help to find out whether measured points are on the terrain or on top of some topographic or manmade objects. Thus a lack of reasoning about possible causalities has to be noticed in these approaches.

To cope with unsatisfactory DTM quality other sensors like laser scanners and radar are taken into account. The discrimination between first and last response of the reflected laser signal contributes to a simplification of the interpretation related aspects of DTM acquisition. But this does not mean that the basic interpretation problem is solved or bypassed with range measurement scanners.

Instead of working with complementary data sources like range data and images more sophisticated algorithms may be developed which is basically the background of the presented work. In the following we propose a method which employs established concepts of hierarchical feature based matching and robust finite element modelling and introduce new ideas based on fuzzy reasoning for feature detection and matching. To deal with imprecise knowledge in the reasoning system the fuzzy logic concept is used. The advantage is that no yes/no decisions are necessary in an early stage of reasoning. The long-term objective of our development is to improve the interpretation related capability of the algorithms, for example, by combining given uncertain prior information about smoothness of a surface with hints about discontinuities or other textural information extracted from the images.

2 OUTLINE OF THE MAJOR PROCESSING MODULES

Coarse-to-fine procession using image pyramids and multi-resolution modelling of DTMs are well-known conceptual aspects of DTM generation procedures. By introducing a fuzzy inference system for DTM acquisition the established modules are taken over and used as a basis of the system. As mentioned before fuzzy logic can be beneficially blended with proven concepts and modules of DTM generation.

The major components of the proposed approach are the following. Detection and matching procedures are started on the top level of the image pyramids. A corresponding rough approximation of the terrain surface might be given or derived using existing ground control points. This surface defines the coarse layer of the DTM pyramid. Projection of the DTM nodes into image space using the given collinearity equations is carried out for the left and the right feature pyramid. This information is used to initiate the matching process and delimit the location and search space for establishing conjugate features. The detection of features as well as feature correspondence are taken into account by employing fuzzy rules. The aspects of fuzzy inference are discussed in detail in the next section.

Transfer of conjugate feature points into object space is carried out by spatial intersection. The calculated object co-ordinates of feature points are used to interpolate a regular grid terrain model based on robust finite element (FE) modelling. Matching and DTM interpolation are executed using coarse-to-fine processing. This results in a progressive densification of the DTM which finally is generated with its highest grid point density.

A refinement of the DTM interpolation process can be developed by taking fuzzy knowledge about the relation of image features and object space modelling into account. A fuzzy rule which relates to all edge points may state that "corresponding edges of the images might be spatial discontinuities in 3D". Obviously this is not true in all cases because there might be more edges which originate from texture, land use, etc. than 3D discontinuity lines. Therefore a further rule stating "if the parallax on one side of an edge is similar to parallax on the other side then this edge will not correspond to a 3D surface discontinuity" may contribute for clarification. These rules which are obviously of fuzzy nature have to be processed by applying fuzzy operators, proper implication methods and aggregation of the outputs. The task of fuzzy reasoning is to work out the different possibilities in an integrative manner. Reasoning and matching have to be re-iterated with 3D FE modelling of the surface. If fuzzy reasoning indicates 3D discontinuities this can directly be taken into account within the FE model by relaxing the continuity constraints for the corresponding locations. Because fuzzy reasoning between image space and object space as indicated above is not fully worked out so far we focus in the following on image space processes based on fuzzy logic and only shortly outline the object space processes based on robust FE modelling. This reflects the current development state of the implemented software.

3 IMAGE SPACE PROCESSES BASED ON FUZZY LOGIC

Image space processing can be assigned to two separate stages: feature extraction and feature matching. In the first stage key points have to be detected and in the second stage key points are matched to obtain conjugate points in two or more images. Because the focus is laid on fuzzy inference processes for extraction and matching some basic ideas on fuzzy reasoning will be reviewed first. Examples of fuzzy inference relating to the implemented detection and matching processes will be presented afterwards.

3.1 Fuzzy Reasoning

Fuzzy inference is the actual process of mapping from a given input to an output using fuzzy logic. The process involves membership functions, fuzzy logic operators, and if-then rules (Zimmermann, 1993). Since the terms used to describe the various parts of a fuzzy inference process are far from standard and the idea is not to explain them all in detail here we try to be as clear as possible about the different terms. A fuzzy reasoning processes may be composed by five parts:

1- *Fuzzification of the input variables*. For each input variable the degree is determined to which it belongs to each of the appropriate fuzzy sets via membership functions. The fuzzy set is a 'container' of elements without a clearly defined boundary. The membership function defines how each point in the input is mapped to a membership value.

2- *Applying fuzzy operators.* If–then rules are those conditional statements which make fuzzy logic useful. The if-part of the rule is called the antecedent (premise), while the then-part is called the consequent (conclusion). If the antecedent of a given rule has more than one part, the fuzzy operator is applied to obtain one number that represents the result of the antecedent for that rule. This number will then be applied to the output function, The output is a single truth value.

3- *Implication.* Before applying the implication method, one must take care of the rule's weight, which is applied to the number given by the antecedent. The implication method is defined as the shaping of the consequent (a fuzzy set) based on the antecedent. It occurs for each rule.

4- *Aggregation of outputs.* Aggregation is a matter of taking all the fuzzy sets that represent the output of each rule and combining them into a single fuzzy set. The unified output of the aggregation process is one fuzzy set for each output variable.

5- *Deffuzification*. The final step is defuzzification. The input of the defuzzification process is the aggregate output fuzzy set and the output is a single number called the crispness.

The illustration of this 5 steps is given in Figure 1. It shows fuzzy inference for the example of matching small patches or points using fuzzy conditions for correlation based similarity and conditions for expected and tolerated parallaxes in image space.

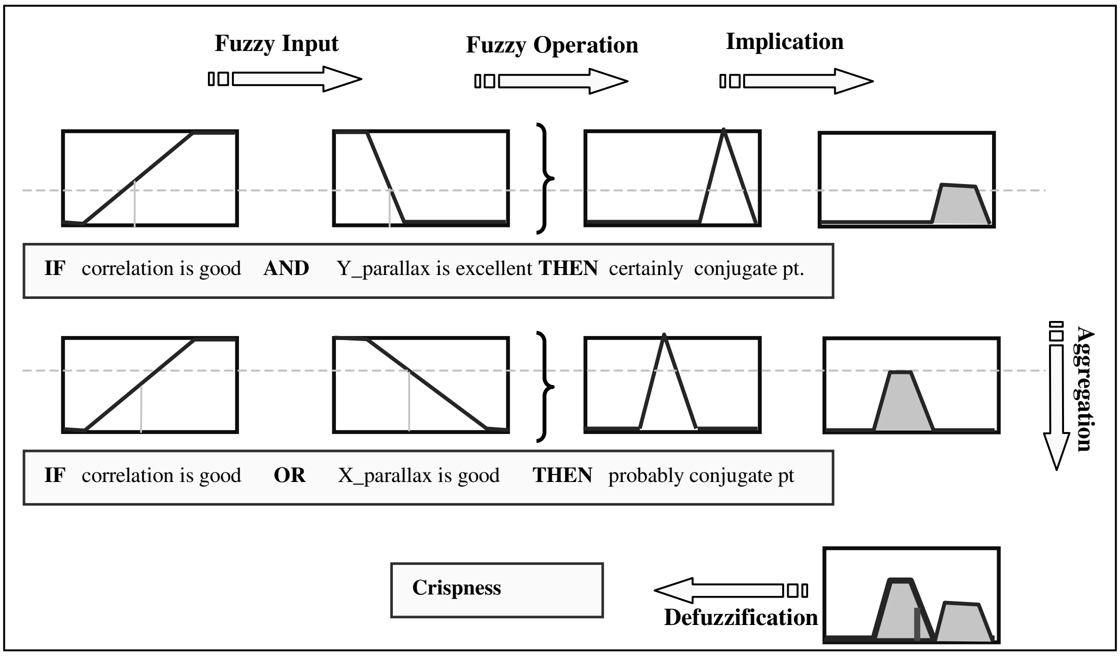

Figure 1: Fuzzy reasoning diagram with an example based on fuzzy knowledge about image correlation and conditions for the X and Y parallaxes

3.2 Detection of Key Points

Key points are points in the images which may take a key role within the overall processing. In particular these are prominent points, edge points or other points which may represent significant texture. In the experiments interest points extracted by Förstner's interest operator (Förstner and Gülch, 1987) are used. Other points in particular edge points have to be integrated into processing at a later stage.

This interest operator can be developed starting with elementary statistical texture parameters like local gradient variances in x- and y-direction. From this parameters a roundness measure and a weight is derived which defines (non) isotropy of texture in the window and the quality of point localisation, respectively.

The selection process involves thresholding of both parameters, the roundness measures and the weights. If, in addition, classification between circular shaped features and junction points is taken into account a further sharp decision has to be made by carrying out a statistical test. In consequence, the results of the detection and classification process of the interest operator might be different sets defined by all isotropic textured windows, by all highly weighted windows, by circular features, by junctions or by general isotropic textures, respectively. In fuzzy set theory these are considered classical sets with a crisp (well-defined or sharp) boundary rather than fuzzy sets.

Theoretically the interest point detection process my be fuzzified by introducing fuzzy sets instead of classical sets and fuzzy rules instead of rules with hard thresholds. But instead of working out exactly such an inference process we want to use additional basic texture measures, in particular, the grey value mean and the grey value variance. Those measures shall be merged with the Förstner operator in a fuzzy reasoning system. In the following some of these criteria and rules are discussed as an example.

Fuzzy Rules in the Detection Process

The following fuzzy rules are applied to interest windows, i.e. only those windows which are already detected and selected by the interest operator by using low thresholds only.

Rule_1:

To avoid interest point extraction in predominantly dark or bright areas (which are also avoided if point selection is carried out by human operators) the mean grey scale in an interest window should be higher than 30 and lower than 230 (Figure 2).

Rule 1. IF *Mean Is Central* THEN *Probably Key Point* ELSE *Probably No Key Point*

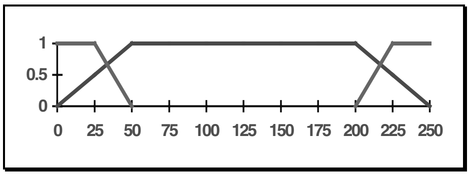

Figure 2: Membership function of mean

Rule_2:

For interest windows the grey scale standard deviation must be above a certain limit (Figure 3). The corresponding rule reads as

Rule 2. IF *Variance Is High* THEN *Probably Key Point* ELSE *Probably No Key Point*

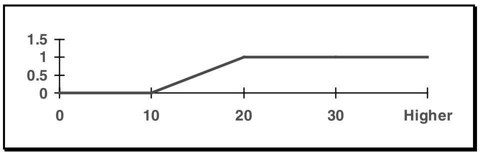

Figure 3: Membership function of variance

Some further rules are formulated which relate to the roundness and the weight measures of the interest operator basically stating that the higher this measure are the higher is the probability for being an key point.

For all these fuzzy if-then rules the linguistic output is "key point". Applying the implication and aggregation steps leads to the following membership function of key points (Figure 4). After defuzzification the resulting key point probabilities are determined. All key points with probabilities higher than 50% are considered as detected points and are plotted in Figure 5. Displayed are the detected points in three different levels of the image pyramid.

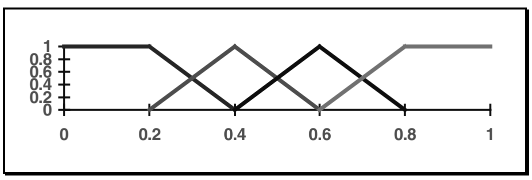

Figure 4: Membership function of key points

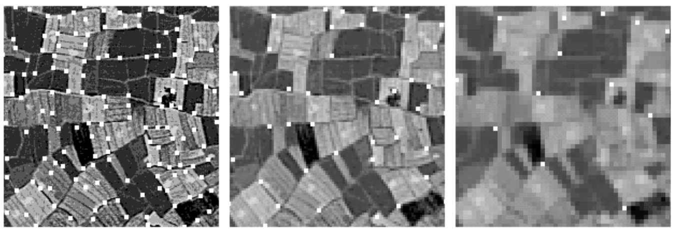
Figure 5: Detected points based on implemented fuzzy reasoning

3.3 Matching of Corresponding Key Points Based on Fuzzy Logic

Another important part of automatic feature based DTM generation is matching of key points. Fuzzy inference can be related to geometrical constraints and to radiometric constraints. Fusion of the constraints of both types leads to a fuzzy reasoning process for finding establishing correspondence.

3.3.1 Geometric Constraints

As outlined previously the matching process takes advantage of multilevel DTM generation and coarse-to-fine processing. The result of this is that an approximate location is predictable for establishing corresponding points. The fuzzy knowledge about the search space and the given orientation of the images can be use to formulate fuzzy matching rules for constraining the search space geometry.

Rule_1:

Given the predicted location of a certain feature point in the second image of an image pair the distance between the predicted locations and the location of extracted point in the search window in X-parallax direction should be small. For convenience this distance is abbreviated as X-distance. A sample for a membership function is plotted in Figure 6.

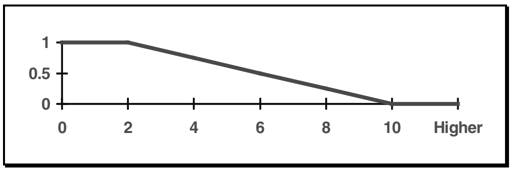

Figure 6: Membership function of *X_Distance*

Rule 1. IF *X_Distance Is Short* THEN *Match* ELSE *Not Match*

Rule_2:

Similar to rule 1 a second rule may apply for the Y-parallax of two points. But given the image orientation or epipolar line geometry the deviation orthogonal to the epipolar line (Y-distance) must be near to zero.

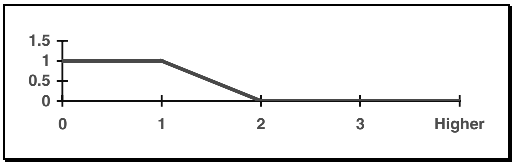

Figure 7: Membership function of *Y_Distance*

Rule 2. *IF Y_Distance Is Small* THEN *Match* ELSE *Not Match*

3.3.2 Radiometric Constraints

These constraints are based on the similarity of the grey values in the neighbourhood of extracted points in different images. Cross correlation values (CC) of the grey scale images and furthermore of local texture descriptions can be taken into account. But other features like local estimates of noise of the SNR are also of interest in this context.

Rule_1:

By correlating grey values, corresponding points should show up with high cross correlation values. A corresponding membership function is plotted in Figure 8.

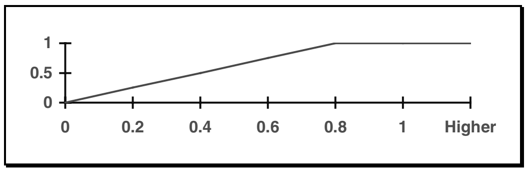

Figure 8: Membership function of *CC*

Rule 1. IF *CC Is High* THEN *Match* ELSE *Probably Not Match*

Rule_2:

Local estimates of the SNR should be similar to for corresponding points. For convenience the differences are abbreviated by S_diff (Figure 9).

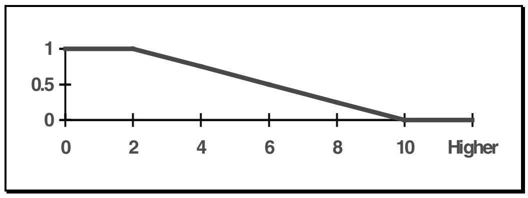

Figure 9: Membership function of *S_Diff*

Rule 2. IF *S_Diff Is Small* THEN *Probably Match* ELSE *Probably Not Match*

Altogether currently 10 fuzzy rules are formulated and used for constraining matching. For all these fuzzy if-then rules of matching the linguistic output is ”corresponding point”. Taking all membership functions into account fuzzy inference will lead to the membership function of corresponding points plotted in Figure 10.

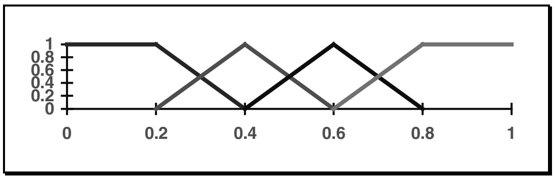

Figure 10: Membership function of corresponding points

After defuzzification the resulting matched point probabilities are determined. All corresponding points with probabilities higher than 50% may be introduced into further processes.

4 OBJECT SPACE PROCESS

Processing in object space basically starts with the co-ordinates of 3D points calculated by spatial forward intersection. From the generally huge number of discrete mass points a continuous surface is approximated by FE modelling. Continuity and smooth transition between neighbouring finite elements is introduced by regularisation. In the implemented procedure a spline based FE model is used.

To deal properly with outliers the least squares estimation process of estimating the terrain surface is robustified. Robust estimation using weight functions and iterative solutions are powerful for big data sets with high redundancy. Because the number of matched points for each DTM grid is generally high, robust estimation is quite successful in carrying out DTM interpolation. Details on those concepts are eg. given in Hahn, 1989 and Ackermann and Krzystek, 1991.

To develop a refinement of this procedure of DTM interpolation with a higher degree of robustness the points should possess a certain semantic meaning. For this purpose the key points should be assigned to fuzzy sets containing, for example, general topographic points, edge points with 3D discontinuities of different order, points which are likely to belong to surfaces of manmade objects or other objects like trees. Rules like those outlined in section 2 have to be developed and integrated in fuzzy inference processes to make the information more explicit which is only incompletely and implicitly available in the images. The assignment to fuzzy sets without the need to be semantically accurate is certainly a benefit for a development based on fuzzy logic.

5 EXPERIMENTS

Some first experiments are carried out with the presented fuzzy method for automatic DTM generation.

The data set used is a mountainous area in the North-Western part of IRAN. The scale of the photographs is 1:10.000, the focal length 150 mm and the length overlap of two stereo images is about 60%. Thus the terrain area imaged in both images covers an area of 1.5km × 3km. The images were scanned by 20µ pixel size by the high precision photogrammetric scanner of Intergraph. Figure 11 shows an overview image of this area.

Obviously this is a very meagre, rocky area. But it is a typical image for the mountainous regions in IRAN showing the challenge for manual DTM data capture as well as for automatic procedures.

Manual measurements are carried out by a very experienced operator using the ParadEyes station, which is a digital photogrammetric workstation. The contour lines

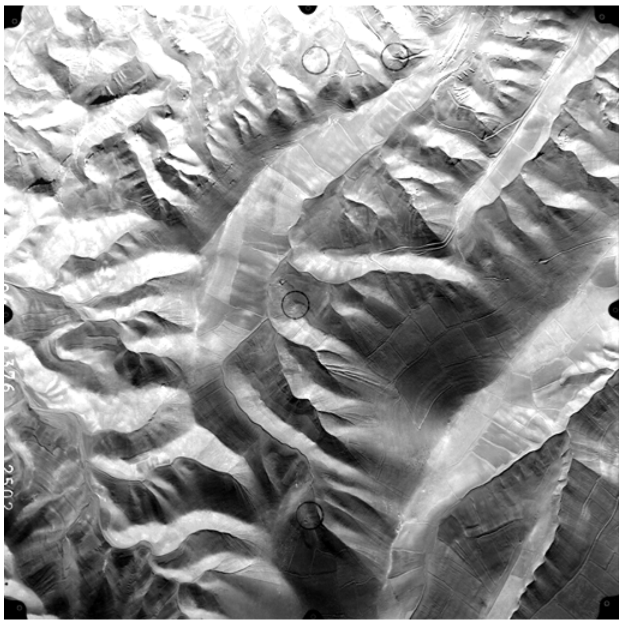

Figure 11: Image used in the experiments

measured manually are shown in Figure 12. This measurements have been carried out for other purposes but can be used in our experiments for visual comparison with the results of the automatic DTM generation.

In addition, a very dense grid is measured manually with a 20m sampling interval. These measurements are taken as a reliable reference for the automatically generated DTM based on the fuzzy reasoning concept presented in chapter 3. A shaded visualisation of the reconstructed DTM is plotted in Figure 13. Even though the scale of both figures does not allow for any detailed comparison the similarity of the morphologic structure of the terrain surface can be well recognised by comparing Figures 12 and 13.

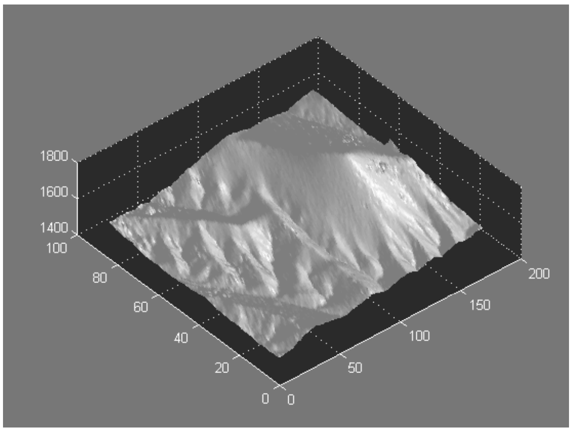

Figure 13: Visualization of the automatically reconstructed DTM

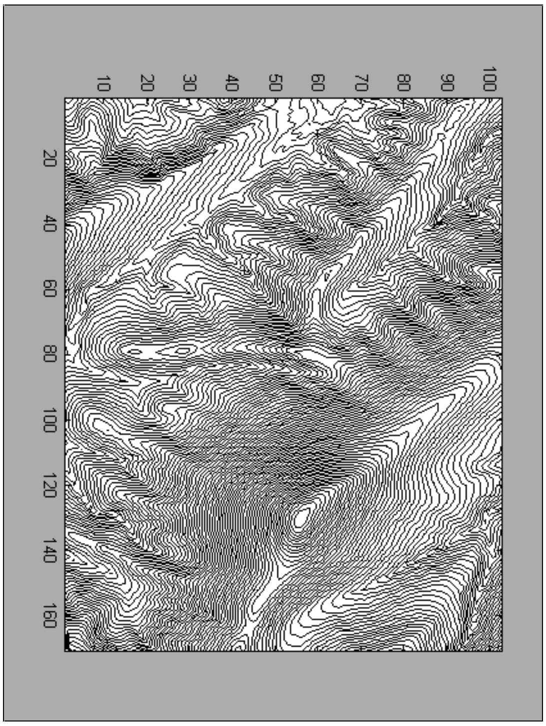

Figure 12: Manually measured contour lines

Some statistical data about point extraction, matching and DTM reconstruction are collected in Table 1. In addition to the 20 µ pixel size (layer 0) five additional layers have been used within coarse-to-fine processing. The respective numbers of points detected by the fuzzy point extraction procedure if given for each layer together with the number of matched points. Typically about 50 to 70% of the points are eliminated by the fuzzy conditions applied in matching.

An indicator for the accuracy of the automatically generated DTM is the rmse calculated by taking the check points into account. The rmse values of the differences of the height of the check points and the DTM heights are indicating an accuracy of 1:2 000 of the flying height which is considered to be a good results facing the low texture available in the images (Figure 11).

	Image Space			**Object Space**		
	Detected Points (left)	Detected Points (right)	Match Points	Number of Check Points	Mean Deviation to Check Points (m)	RMSE to Check Pts(m)
Layer 5	489	422	226	11543	-5.916	12.558
Layer 4	1927	1759	900	11543	-1.886	6.003
Layer 3	8178	7250	3486	11543	-0.708	3.495
Layer 2	33817	30025	13509	11543	-0.386	1.966
Layer 1	134925	122252	51212	11543	-0.208	1.381
Layer 0	533648	490245	170267	11543	-0.111	0.763

Table 1: Statistics on point extraction , matching and DTM reconstruction in the test area

Altogether we do not want to overrate the results of this first test with our new fuzzy reasoning approach for DTM reconstruction. But with this experiments we could show that the developed method has the capability to acquire DTMs even in difficult terrain.

6 CONCLUSIONS

The goal of the presented work was to develop a new approach for DTM reconstruction based on fuzzy reasoning. Fuzzy logic offers the theoretical framework on which processes of fuzzy nature can be build. Fuzzy inference processes allow to utilise a variety of constraints by formulating proper fuzzy rules. Corresponding algorithms for point feature extraction and for matching have been developed and presented. These algorithms are embedded into an overall process for DTM reconstruction

First experiments are carried out which show the applicability of the developed and implemented procedure. This first success encourages to extend the fuzzy framework by including the object based reconstruction modules in fuzzy inference processes. Some ideas about refining DTM generation by relating image feature extraction and surface modelling are outlined in the paper. A detailed elaboration of the corresponding fuzzy rules are left for future work.

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