LINEAR FEATURES EXTRACTION BY STRING MATCHING FOR AUTOMATIC DEM GENERATION

King-Chang Lo
Professor, Institute of Survey Engineering,
National Cheng Kung University, Taiwan, Republic of China

Commission III, Working Group 2

KEY WORDS: Features Extraction, String Matching, Cost Function, DEM Generation

ABSTRACT:

According to the strategy "refinement from coarse" for automatic DEM generation, highly reliable coarse DEM data need to be produced first. We start with image conditional smoothing to remove minor features or noise by non-linear filter, e.g., the conditional rankorder filter. Then we use a gradient filter to detect the pronounced linear features in each epipolar line at the zero crossing of the grey value function, then, a string of pronounced linear features have been detected along the conjugated epipolar lines, but these are not always found to correspond to each other because different terrain situations give different reflections. To solve this problem, an algorithm called string matching must be found to confirm and extract the real corresponding feature pairs based on the theory of minimum cost sequence of error transformations. By applying string matching at feature level rather than signal processing level to extract the corresponding feature pairs in conjugated epipolar line pairs, we confirm the extracted linear features again by checking the continuation of linear features between neighbouring epipolar lines, the reliability can be increased still more. These extracted corresponding linear feature pairs can be used to generate a coarse DEM. The major requirement for generating a coarse DEM with high reliability is then fulfilled. Based on these high reliable coarse DEM as good conjugacy position prediction, the refinement process, such as object space least squares matching, can be done for high quality DEM generation.

1. INTRODUCTION

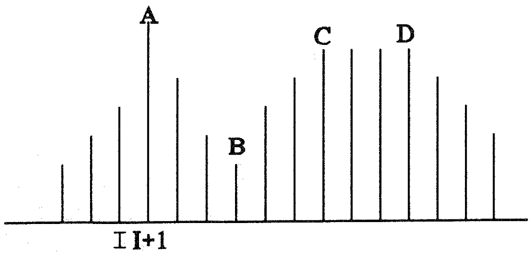
Based on the strategy "coarse to fine" for DEM generation, highly reliable coarse DEM data need to be produced first. Not only the edge features of homogeneous intensity regions and uniform texture regions can be used for coarse DEM generation [Lo,1993], but also the linear features. Therefore, the string matching of linear features is presented for coarse DEM generation.

We start with image conditional smoothing to distinguish the linear features and reduce minor features or noise by non-linear filter, e.g., the conditional rankorder filter [Mulder & Sijmons,1984]. A gradient filter is used to detect the pronounced linear features in each epipolar line at the zero crossing of the grey value function, and apply string matching at feature level rather than signal processing level to extract the corresponding feature pairs in conjugated epipolar line pairs. These conjugated feature pairs are used for producing coarse DEM and then be refined by a high accuracy matching method, such as, object space least squares matching [Wrobel,1987;Heipke,1992].

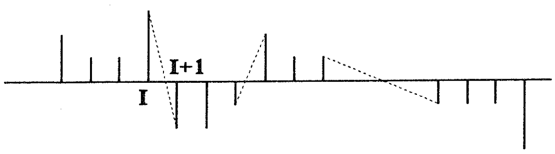
2. LINEAR FEATURES DETECTION

As a result of the conditional rankorder operator, pronounced linear features show up as a string along an epipolar line. Convolution of the image with a gradient filter [1,-1,0] gives the zero crossing phenomenon when linear features exist (Fig. 1).

In Fig. 1a, there are linear features which show up as peaks and valleys. From Fig. 1b, the properties (attributes) that can be obtained for linear features are:
(a) the position (PS) of the peak/valley which is located at position I+1 of the zero crossing I(+) to I+1(-) or I(-) to I+1(+) (this implies a Laplacian filter effect)
(b) the slope at the front (SF) of the peak/valley and the slope at the back (SB) of the peak/valley which can be obtained at positions I and I+1 in Fig. 1b. An additional property is the grey level (GL) of the peak/valley which can be obtained at the position of the peak/valley in previous conditional rankorder smoothing image file (Fig. 1a).



(a) Linear feature string A,B,C,D along epipolar line after applying conditional rankorder operator



(b) Result from convolution with gradient filter [1, -1, 0] which indicates the position of linear features at zero crossing

Fig. 1: Linear feature detection with a gradient filter and zero crossing

3. LINEAR FEATURES EXTRACTION BY STRING MATCHING

After applying conditional rankorder operations to remove minor features or noise, and a string of pronounced linear features have been detected along the conjugated epipolar lines, these are not always found to correspond to each other because different terrain situations give different reflections. To solve this problem, an algorithm must be found to confirm and extract the real corresponding feature pairs based on the similarity assessment by the theory of minimum cost sequence of error transformations (cost function minimization).

There are two ways to assess the similarity measure by using the cost function: distance measure approach and conditional probability approach. The distance measure could be the absolute differences of attributes of two corresponding primitives, therefore, the distance measure approach performs in a reasonable manner with numeric attribute values and it is the reason why we choose it as similarity measure. If the attribute values of primitives are symbolic, such as straight or curve for a line primitive, it is hard to justify the assignment of the costs for different symbolic attributes, then the conditional probability approach is more suitable for applying [Boyer & Kak,1988].

The cost of error transformation is estimated in terms of distance in characteristic space (attribute space). The dimension of this characteristic space is determined by the number of attributes of the primitives in the property list. The property list consists of the attributes of linear features such as position, amplitude and shape of the peak/valley in intensity profile along the epipolar line pairs [Lo,1989], and the orientation of linear features [Kostwinder et al.,1988]. According to this property list, a characteristic function (cost function) is formed, which should be sensitive enough to measure the similarity between two linear features. One possibility is to use a string-to-string matching algorithm which has been applied to seismic image skeletonization [Lu,1982], bearing in mind that seismic waveforms can more simply and more easily be defined than terrain images. According to the reliability of attributes and their major/minor contribution to measuring the characteristics of linear feature, different weights are assigned to the individual attributes in the cost function, thus offering a criterion for correspondence analysis.

We build up the cost function for estimation of the "cost" of error transformation (we define the "cost" as distance) between two peaks/valleys on R (right image) and L (left image):

$$d(R,L) = W_1 * |PS_R - PS_L| + W_2 * |GL_R - GL_L| + W_3 * |SF_R - SF_L| + W_4 * |SB_R - SB_L| \tag{1}$$

The W_i (the weight of attributes) can be assigned by prior analysis or in an experiment by trial and error.

Using this cost function, we calculate the distance d(R,L) (as a similarity measurement) between the first linear feature of one epipolar line and all linear features of corresponding epipolar lines, then between the second feature and all features of corresponding epipolar lines, and so on. For the conventional matching strategy, the target area of the left image is selected to search for the best match in the search area of the right image only; the result may be different, however, if the matching is from right to left. String matching uses the mutual matching strategy, which matches not only left to right but also right to left, and then selects the minimum cost among them as the best matching and extracts it. If we confirm the extracted linear features again by checking the continuation of linear features between neighbouring epipolar lines, the reliability can be increased still more. Between conjugated epipolar line pairs, the corresponding linear feature can be extracted by string matching, which uses the minimum cost as best matching. The extracted corresponding linear feature pairs can be used to generate a coarse DEM. The major requirement for generating a coarse DEM with high reliability is then fulfilled.

To explain the procedure of string matching more easily, we have designed a simplified example, taking the position of the linear features from the property list only and simplifying the cost function as: $d(R,L) = 1^* |PS_R - PS_L|$, we can then generate the distance matrix shown in Table 1. To avoid the same value being shown up in distance, we assume some non-integer values for position.

Table 1: Distance matrix generated from cost function

Distance		Position in Right Image								
		1.0	2.0	3.1	5.0	6.0	7.0	8.1	10.0	12.0
Position in Left Image	2.0	**1.0**	**0.0**	1.1	3.0	4.0	5.0	6.1	8.0	10.0
	4.0	3.0	2.0	**0.9**	1.0	2.0	3.0	4.1	6.0	8.0
	5.0	4.0	3.0	1.9	**0.0**	**1.0**	2.0	3.1	5.0	7.0
	8.0	7.0	6.0	4.9	3.0	2.0	**1.0**	**0.1**	2.0	4.0
	9.0	8.0	7.0	5.9	4.0	3.0	2.0	**0.9**	**1.0**	3.0
	10.0	9.0	8.0	6.9	5.0	4.0	3.0	1.9	**0.0**	2.0
	12.0	11.0	10.0	8.9	7.0	6.0	5.0	3.9	2.0	**0 0**

In this distance matrix, we first search column by column and then row by row for the smallest distance, and then put it into the smallest distance map which has been initiated with value -9 (Table 2).

Table 2: Minimum distance map

		Position in Right Image									
		1.0	2.0	3.1	5.0	6.0	7.0	8.1	10.0	12.0	Column for Marking
Position in Left Image	2.0	1	0	-9	-9	-9	-9	-9	-9	-9	1
	4.0	-9	-9	0.9	-9	-9	-9	-9	-9	-9	1
	5.0	-9	-9	-9	0	1	-9	-9	-9	-9	1
	8.0	-9	-9	-9	-9	-9	1	0	-9	-9	1
	9.0	-9	-9	-9	-9	-9	-9	0.9	-9	-9	-1
	10.0	-9	-9	-9	-9	-9	-9	-9	0	-9	1
	12.0	-9	-9	-9	-9	-9	-9	-9	-9	0	1
		-1	1	1	1	-1	-1	1	1	1	
	Row for Marking										

if more than one minimum distance appears in one row/column of the minimum distance map, it means that some extra feature exists (i.e., there are one-to-many correspondences). Therefore, we need to select the very smallest as the best matching feature (marked 1 in the marking column/row and -1 on the extra linear feature). For example, in Table 2, for position 2.0 in the left image, there are two candidates in the right image (see row 1: 1 and 0), giving -1 and +1 in the marking row to indicate the extra candidate and the best matching candidate.

According to the marking, we can extract the corresponding features from each set of conjugated epipolar lines. As a result of this principle, the final matching scheme is indicated by the arrows in Table 3.

Table 3: Marking and extraction of best matching feature pairs

position in right image								
1.0	2.0	3.1	5.0	6.0	7.0	8.1	10.0	12.0
-1	1	1	1	-1	-1	1	1	1
	2.0	4.0	5.0	8.0	9.0	10.0	12.0	
	1	1	1	1	-1	1	1	
position in left image								

4. IMPLEMENTATION

The cost function used in the string matching algorithm will involve several attributes of the linear features, but the corresponding weight assignment will be the critical parameter for correct matching. Several experiments need to be carried out in order to get the correct weighting for the various attributes. Based on our knowledge of the influence of these various attributes on the matching process, the conclusion reached was to assign weights to the attributes in proportion to their reliability and the derived magnitude which expresses their similarity (e.g., $|PS(I)-PS(J)|$, $|SF(I)-SF(J)|$, etc.), so regulating the influence of each attribute that in the result poor attributes will not overcome good attributes. As a result of aerial triangulation and the possibility of providing the system with good provisional positions of conjugated points, a higher weight was assigned to the position attribute ($|PS(I)-PS(J)|$) than to other attributes. On the other hand, attributes which are related to the grey level are given a smaller weight mainly due to a lack of reliable information about the scanning characteristics, terrain characteristics etc. As an example, the following cost function was chosen:

If it is peak-to-peak or valley-to-valley :

$$d(I,J) = 1^*|PS(I)-PS(J)| + 0.05^*|SF(I)-SF(J)| + 0.05^*|SB(I)-SB(J)| + 0.01^*|GL(I)-GL(J)| \tag{2}$$

If it is peak-to-valley or valley-to-peak:

$$d(I,J) = -[1^*|PS(I)-PS(J)| + 0.05^*|SF(I)-SF(J)| + 0.05^*|SB(I)-SB(J)| + 0.01^*|GL(I)-GL(J)|] \qquad (3)$$

The magnitude of the peak/valley is a very important characteristic to be used even if its value is not so reliable. Although peaks cannot match with valleys, we cannot give the amplitude of a valley a minus value or it would destroy the characteristic of the function model, which is mainly controlled by the position feature. The alternative found was to still treat the amplitude of a valley as a positive value but change the sign to minus for the resulting distance and use its absolute value for searching the smallest value. This means that we can still keep the candidacy of a valley which would be matched by the peak, but which we would never allow to happen. This would stop the peak trying to match the other peaks behind the valley and would occupy the chance of another pair to match (in Fig. 2, let peak c still matches valley d, otherwise peak c would match f and prevent e from matching f). This is very useful for correct matching in dense peak/valley situations.

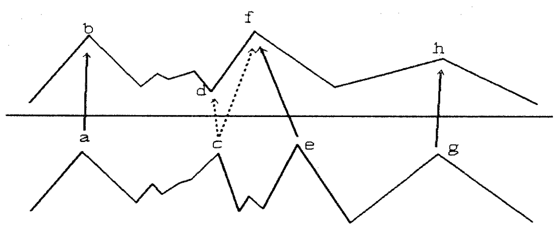


Fig. 2: Keeping the "peak-to-valley" matching to avoid mismatching

Since most of the time a valley shows up after a peak (or vice versa), it is also a form of powerful control. The way of judging the quality of the cost function model is to analyze the distance matrix. It will be a bad cost function model if the positions of the smallest distance values are distant from the diagonal axis of the matrix and their values are rather large.

The marking technique should be improved to avoid leading to one-to-many matching in cases where we only apply the simple marking technique mentioned before (mark +1 in the marking column/row for the minimum distance you want to reserve, mark -1 for the one you want to abandon). By examining the results of the experiment carefully, we can detect the difficult situations where simple making techniques will lead to incorrect results (Fig.3).

	Minimum Distance Map	Marking Column
	1 2 3	+1 +1 -1
Marking row	+1 -1 +1	

Case 1
wrong marking

2 1 3	+1 -1
-1 +1 +1	

Case 2
correct marking

1 2 3	+1 -1 +1
+1 +1 -1	

Case 3
wrong marking

1 3 2	+1 -1 +1
+1 -1 +1	

Case 4
wrong marking

Fig. 3: The cases where simple marking techniques lead to incorrect results

In Fig. 3, there are three possible cases which might lead to one-to-many matching. These cases are presented by their minimum distance map and marking column/row. In the first case, searching the first row leads to mark [+1,-1] in the marking row; searching the second row however leads to a change in the first decision (i.e., the -1 mark becomes +1), which leads to one-to-many matching situations. A similar problem is shown in cases 3 and 4. The ambiguity comes from the case where the element is "abandoned" during the sorting of the previous column/row and is then reassigned "reserved" status. Thus, the principle of marking would be that once the element has been "abandoned", there is no way to change it back to be "reserved". Therefore, the marking technique is so modified that we initial all elements of marking column/row with 0, then we add 1 (instead of replacing the marker by +1) to the element that has to be reserved, but we subtract a large number (instead of replacing the marker by -1) from that element if it has to be abandoned. From experiments, this large number is assigned to be 3, because there should be no more than three "candidates" in one column/row if the cost function model is good enough.

As the linear features should show up continuously in adjacent epipolar lines, the matching pairs between adjacent epipolar lines are compared with each other. If the differences in position of both corresponding elements are small and equal to three pixels in size (because the location of the detected linear feature cannot be defined very exact from a complex terrain image after applying the conditional rankorder operator), we keep this as the final reliable result. If some mismatching results caused by the noise or salient points still exist, we can use this characteristic to confirm the real linear feature and get rid of the false matching pairs.

The result of string matching was found to be highly reliable. The accuracy is not as high as intensity-based matching, but it can offer good enough pull-in range for later refinement by object space least squares matching.

5. RESULTS OF EXPERIMENT

(1) For epipolar lines resampling, relative orientation is performed with Kern DSR-1 and rotation elements of left/right images are obtained. After the epipolar lines resampling, the conditional rankorder filter is applied to remove minor features and part of noise (Fig. 4).

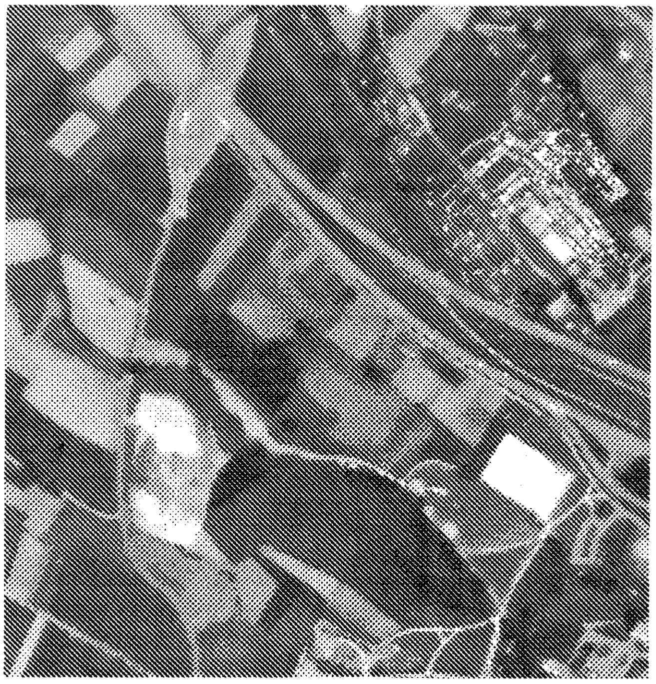


Fig. 4: The left image after epipolar lines resampling and conditional rankorder filter

(2) For linear features detection, the gradient filter is applied and linear features are located by zero crossing. (Fig. 5)

(3) By string matching, the false linear features which show up in one image only are removed, and the conjugated linear features which show up in both left/right images are extracted. (Fig. 6). According to these useful conjugated linear features pairs, the coarse DEM data can be produced.

Fig. 5: The raw linear features detected by gradient filter (left image)

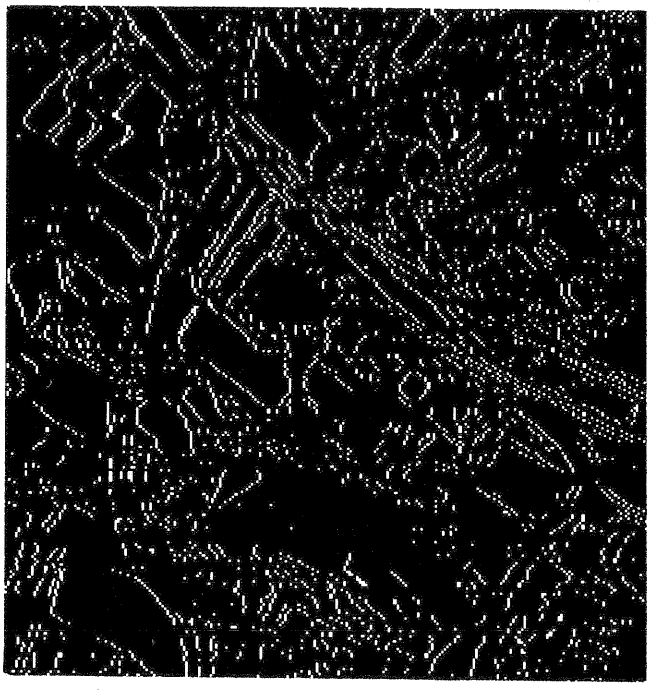


Fig. 6: The useful linear features extracted by string matching (left image)

6. DEM GENERATION

After string matching, the conjugated point pairs along the linear features are extracted and space intersection is applied to generate coarse DEM data. The height information (disparity) of these linear feature points is used as the predicted conjugated position, Based on these coarse DEM data which offer sufficient pull-in range, object space least squares matching can be performed for accuracy refinement, the matching would start at predicted conjugate position which would not lead to mismatching, and the time of image matching would be reduced also, thus increasing the efficiency of fine DEM generation, and the high quality DEM data can be obtained at the end.

The traditional method uses window of pixels for matching to determine a single point (usually the middle point) only, but object space least squares matching uses a window of pixels for matching to determine multi-points in a grid pattern DEM in one solution [Lo,1994]. The high contrast pixels (linear features) would offer a larger contribution to the decision making, helping to avoid making the wrong decision in the homogeneous part of the image. Thus, a combination of the advantages of feature-based matching and intensity-based matching can be obtained for DEM generation.

7. CONCLUSION

(a) Feature-based matching is performed at feature level rather than signal processing level which would not be influenced by geometric distortion and radiometric distortion if we do matching in image space rather than object space. Therefore, by applying string matching to extract the corresponding linear feature pairs in conjugated epipolar line pairs is a robust approach and the results are highly reliable.

(b) For the conventional matching strategy, the target area of the left image is selected to search for the best match in the search area of the right image only; the result may be different, however, if the matching is from right to left. String matching uses the mutual matching strategy, which matches not only left to right but also right to left, then the selection of the minimum cost among them is the " really best matching".

(c) There are two ways to assess the similarity measure by using the cost function: distance measure approach and conditional probability approach. The distance measure approach is applied if the attributes of primitives are numeric. If the attribute values of primitives are symbolic, then the conditional probability approach can be applied still. Therefore, the cost function is a universal approach for solving correspondence analysis problem.

REFERENCES

Boyer, K.L./Kak, A.C. [1988]: Structural Stereopsis for 3-D Vision. IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.10, No.2. 144-166.

Heipke, C. [1992]: A Global Approach for Least Squares Image Matching and Surface Reconstruction in Object Space. PE&RS: Vol.58, No.3, 317-323.

Kostwinder, H.R./Mulder, N.J./Radwan, M.M. [1988]: DEM Generation from SPOT Multiple View Images using Correspondence Analysis. ISPRS 16th Congress, Kyoto. Com.III, III.442-449 (B11).

Lo, K.C. [1989]: Image Quality Assessment for Automatic Production of DEM Data. Conference of Photogrammetry Automation, Tainan, Taiwan. J1-J20.

Lo, K.C. [1993]: Image Segmentation for Region Matching. Journal of Surveying Engineering, Vol.35, No.2, 63-81.

Lo, K.C. [1994]: High Quality Automatic DEM Generation from Multiple Image. Doctor Thesis. Twente University. The Netherlands.

Lu, S.Y. [1982]: A String to String Correlation Algorithm for Image Skeletonization. Proc. of 6th International Conference on Pattern Recognition, IEEE. 178-179.

Mulder, N.J./Sijmons, K. [1984]: Image Segmentation using Conditional Rankorder Filtering. ISPRS 15th Congress, Rio de Janeiro. Com.III.

Wrobel, B.P. [1987]: Facet Stereo Vision (FAST Vision) - A New Approach to Computer Stereo Vision and to Digital Photogrammetry. Conference on Fast Processing of Photogrammetric Data, Interlaken, 231-258.