A NOVEL ERROR DETECTION TECHNIQUE FOR AUTOMATICALLY GENERATED DIGITAL ELEVATION MODELS

M.J. Gooch[1] and J.H. Chandler[2]
1. Cartographical Surveys Ltd, The Survey Centre, Waterworks Road, Worcester, WR1 3EZ, UK.
m_j_gooch@hotmail.com

2. Department of Civil and Building Engineering, Loughborough University, Loughborough, LE11 3TU, UK
J.H.Chandler@lboro.ac.uk

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ABSTRACT
The generation of Digital Elevation Models (DEMs) is one photogrammetric process that has been successfully automated. However, a common criticism surrounding DEM generation software currently available commercially, is the lack of quality assessment procedures. This paper describes a new system called the Failure Warning Model (FWM), which automatically detects low accuracy areas and presents the information in a graphical format that is easy to assimilate.

The technique makes use of the strategy parameters embedded within many current digital photogrammetric systems. Typically, these are a set of user definable parameters that control the search, acceptance and quality control procedures used to derive final point elevations in the DEM. Detailed tests revealed that accurate points are insensitive to changes to the strategy parameters and so the system identifies points that are sensitive to parameter change, which may therefore be considered unreliable. As a further refinement, the algorithm considers the impact of local slope angles and the internal classification of the height estimate.

The Failure Warning Model was developed within the ERDAS Imagine environment for the ERDAS Ortho*MAX* DEM generation software. It was tested on a wide variety of imagery (scale: 1:70 to 1:45,000) representing a variety of land-cover types and show that the approach is successful. More significantly, the method proved successful using other digital photogrammetric systems, indicating the generality of the approach. The Failure Warning Model is described in this paper and combined with results from extensive tests using both the Ortho*MAX* and Phodis TS software from Zeiss.

1 INTRODUCTION

With the advent of computers and their use in the photogrammetric industry, there has been a constant trend towards full automation of the workflow. Developments in digital photogrammetry combined with the dynamic nature of both the computer hardware and software industries, has strengthened this trend even further. As the level of automation increases, the technology is becoming used by a wider and a more novice user base (Chandler, 1999). A common criticism articulated in recent literature comments upon the lack of quality control procedures in modern digital photogrammetry systems (DPS). Such technology allows an answer to be obtained easily (i.e. a digital elevation model or DEM), but provides little help in assessing the quality of the output (Cooper, 1998). As Heipke (1999, p81) states: "most of the ... algorithms have only little knowledge about when they work correctly and when they fail." This issue becomes increasingly relevant as the level of automation increases and as more non-photogrammetrists begin to use the techniques. The research work presented in this paper partially answers this call, through the development of an algorithm known as the "Failure Warning Model". This novel method allows unreliable points to be detected in an automatically generated DEM.

2 AUTOMATED DEM EXTRACTION

A common feature of many digital systems is a set of parameters that allow the user a degree of control over the automatic DEM generation process. These parameters are user-definable and control the acceptance and quality control functions in the software. (e.g. different levels of interpolation can be used). The exact effect of these parameters upon the derived DEMs will differ, but Zhang and Miller (1997) suggest that appropriate settings are functions of terrain type, signal power, flying height, x and y parallax, and image noise level. In theory therefore, a correct set of parameters will provide an accurate DEM, one which consists of successfully correlated points only and where unsuccessful point matches have been rejected. Conversely, an incorrect parameter set will result in either the filtering of successful points, the inclusion of badly correlated points (known as false fixes) or will simply fail to find correlated points (Gooch *et al.*, 1999).

2.1 Erdas Imagine/Ortho*MAX*

One example of a DPS with provides a set of user-definable parameters is the ERDAS Imagine Ortho*MAX* software (ERDAS, 1994) which uses an area correlation based algorithm with 14 strategy parameters. A full list of the strategy parameters and their default values are shown in Table 1. From their individual names and descriptions in the user-manual, it is not always obvious what the parameters mean, or what effect each would have on the resulting DEM. Smith and Smith (1996, p523) state that the "...parameters are written in a technical language and, even if the basic image matching technique is understood, it does not always help in determining the use of all the parameters, as many are obviously software dependent." Loodts (1996) criticizes the use of "...uncontrollable" or "magic" strategies..." in automatic DEM algorithms, but provides no details upon how to specify and control the parameters. Other DPSs use different sets of parameters and terminology. For example, the Match-T product has 28 parameters (Smith and Smith*,* 1996) whilst the Phodis TS software from Carl Zeiss uses just two. The correct choice of parameters should accept all of the successfully correlated points and filter out the unsuccessful and the wrong choice can have a detrimental effect on the accuracy (Gooch and Chandler, 1998). The choice of parameter settings can therefore be critical in generating as accurate a DEM as possible.

Parameter	**Value**
Minimum Threshold	0.6
Noise Threshold	0.4
Maximum Parallax (x)	5
Minimum Template Size	7
Maximum Template Size	9
Minimum Precision	0.5
Rejection Factor	1.5
Skip Factor	2
Edge Factor	2.5
Start RRDS	4
End RRDS	0
y-Parallax Allowance	0
Resampling	Bilinear
Post Processing	On

Table 1. Strategy parameters used in in the ERDAS Imagine OrthoMAX software

Several studies on the effect of parameter settings on DEM accuracy have been completed, including Smith (1997) who carried out an extensive study of the parameters using two sets of aerial imagery. He isolated areas with different land-cover types on the imagery and then systematically varied the parameters, with the aim of optimizing them with respect to accuracy. The results indicated that the manipulation of the parameters could have a significant effect. For example, in one residential area, changing the Minimum and Maximum Template sizes from the default values of seven and nine pixels to five and 20 respectively, improved the mean error of the DEM from -0.218 m to -0.081 m. Similarly, changing the Maximum Parallax parameter from the default value of five to 10 in an area of open moorland improved the mean error from -0.061 m to 0.006 m. Overall, Smith (1997) reported that the software was well suited to smooth, textured surfaces and that areas with sudden elevations changes reduced the accuracy. He suggests that the test results could be applied to other data sets, but makes no recommendations upon how they could be applied to close-range type applications such as medical and architectural imagery.

3 THE FAILURE WARNING MODEL

The Failure Warning Model originated from a series of extensive tests that were developed from the work of Smith (1997). These tests will be described briefly in this section, and demonstrate the basic phenomena underlying the model. Exhaustive tests were carried using Erdas Ortho*Max* to prove the validity of the approach, and are presented also. This is followed by a series of tests carried out using the Carl-Zeiss Phodis software, which importantly demonstrate the universality of the Failure Warning Model.

3.1 Origins of The Failure Warning Model

A series of tests were carried out by the authors on the strategy parameters used in the ERDAS Imagine Ortho*MAX* software, using a variety of imagery with vastly different scales and image content than carried out in Smith's (1997) study. The aim of these initial tests was to quantify the effect of varying the strategy parameters on the accuracy of the DEM. The data sets used in the study included:

- 1:45,000 scale imagery of a dry riverbed in Spain captured using a Kodak DCS420 digital camera.
- 1:25,000 scale imagery of a mountain region of Antarctica scanned at 30 microns.
- 1:13,000 scale imagery of a rural and residential area scanned at 30 microns.
- 1:6,000 scale imagery covering a wide variety of land-cover types captured with a Zeiss RMK A metric camera.

- 1:70 scale imagery of a simulated riverbed constructed in a laboratory. The imagery was captured using a Kodak DCS460 digital camera.

A prerequisite for each data set was that check data was available, thus enabling the parameters to be optimized with respect to accuracy. Optimization of the parameters was carried out using a "trial and error" approach because it was found that two optimum parameter settings did not always combine in a positive manner. The process was thus time consuming and certainly not practicable in a production environment.

Table 2 shows the effect upon accuracy (r.m.s.e.) after changing strategy parameters for five different DEMs. Area 1, 2, 3 and 4 were derived using the same set of imagery (1:13,000 scale photography) whilst Area 5 was generated using a set of 1:6,000 scale imagery. These results are typical of all of the results encountered and demonstrate that specification of the strategy parameters is critical and can have a significant effect on the accuracy of a DEM in certain areas (areas 2, 3, 4, 5 in the example). The results of these tests showed no evident link with landcover type as suggested by Smith (1997).

Area & Landcover type	**r.m.s.e. (m) Para. set a**	**r.m.s.e. (m) Para. set b**	**r.m.s.e. (m) Para. set c**	**r.m.s.e. (m) Para. set d**	**r.m.s.e. (m) Para. set e**	**r.m.s.e. (m) Para. set f**
Area 1- Rural	3.466	3.354	3.327	3.242	3.234	3.568
Area 2- Rural	1.538	1.671	10.952	1.495	1.527	1.793
Area 3- Residential	2.542	3.738	2.529	2.287	3.271	3.532
Area 4- Rural / Forest	3.590	9.845	1.912	3.339	3.12	2.267
Area 5- Urban	2.034	6.030	2.658	2.078	1.87	1.932

Table 2. Results of manual strategy parameter manipulation process.

Similar tests were also carried out using four areas visible on a set of close-range images, (1:70 scale) representing a simulated riverbed or flume and these tests produced a contradiction that was highly significant for this research project. The results showed that in three of the four test areas, alterations to the strategy parameters had little or no effect on the resulting r.m.s.e. of the DEM. However, for one of the test areas, every parameter change appeared to generate a significant change in the r.m.s.e. It was decided to establish why this contradiction had occurred, by examining residuals at individual checkpoints. This demonstrated that only very few of the points contained high residuals and that these were located in just one small region of the check profile. The large variation in the overall r.m.s.e was therefore attributable to varying height estimates at these limited locations only. This finding was then confirmed using the previous data sets, by removing the checkpoints with large residuals from the r.m.s.e calculations, and this again showed that the r.m.s.e was not only low (as expected) but also subject to minimal variation with parameter changes. This demonstrates that the exact strategy parameter settings are not critical, for those points whose elevations have been estimated accurately.

It was then thought that this important finding could be perhaps used to develop a tool that would automatically identify low accuracy areas in an automatically generated DEM. The hope being that such a facility would allow the (novice) user to perhaps manually edit/measure the low accuracy areas, instead of carrying out extensive checks over the entire DEM.

3.2 Basis of The Failure Warning Model

The basic algorithm behind the Failure Warning Model (FWM) is comparatively simple. Initially, two DEMs of the same area are generated using slightly different strategy parameter settings. The two DEMs are then subtracted from one another and points that are assigned a value approximating to zero are clearly insensitive to changes in the strategy parameters, and may therefore be considered reliable. As a further refinement, the algorithm then considers the impact of local slope angles and the origin of the height estimate. In situations where the local slope angle is below a certain threshold and the original height estimate has been interpolated from surrounding points, it is judged that the height estimate, although interpolated, is likely to be accurate also. Points that have been interpolated but are in regions of locally varying topography are judged to be unreliable. Points that have not been interpolated and failed the initial test (i.e. all other points) are considered inaccurate. This three-way classification is then presented in a graphical way, by overlaying the classification upon an orthophoto of the area.

To summarize, each point in the original DEM is given one of three classifications in the output (Figure 1):

- "0" (dark brown areas): areas where the software has interpolated the elevation in areas where slope angle is varying rapidly- Unreliable points;
- Acceptable/OK/Unclassified (orthophoto visible): the evidence from the data suggests that the height estimate of this point is as accurate as possible and is therefore reliable;

- "256" (pink areas): the points with the lowest accuracy. These are the points that are susceptible to changes in the strategy parameters.

The model was developed in the Spatial Modeler tool in ERDAS Imagine, which is a visual modeling environment that allows generation and customization of algorithms to manipulate graphical data. The software allows for a wide variety of inputs including raster, numeric, and vector files with output to a similar range of file types.

The inputs for the FWM are as follows:

- DEM generated with the default strategy parameters
- DEM generated with a different set of strategy parameters (four parameters were changed in these tests)
- An orthophoto of the area.

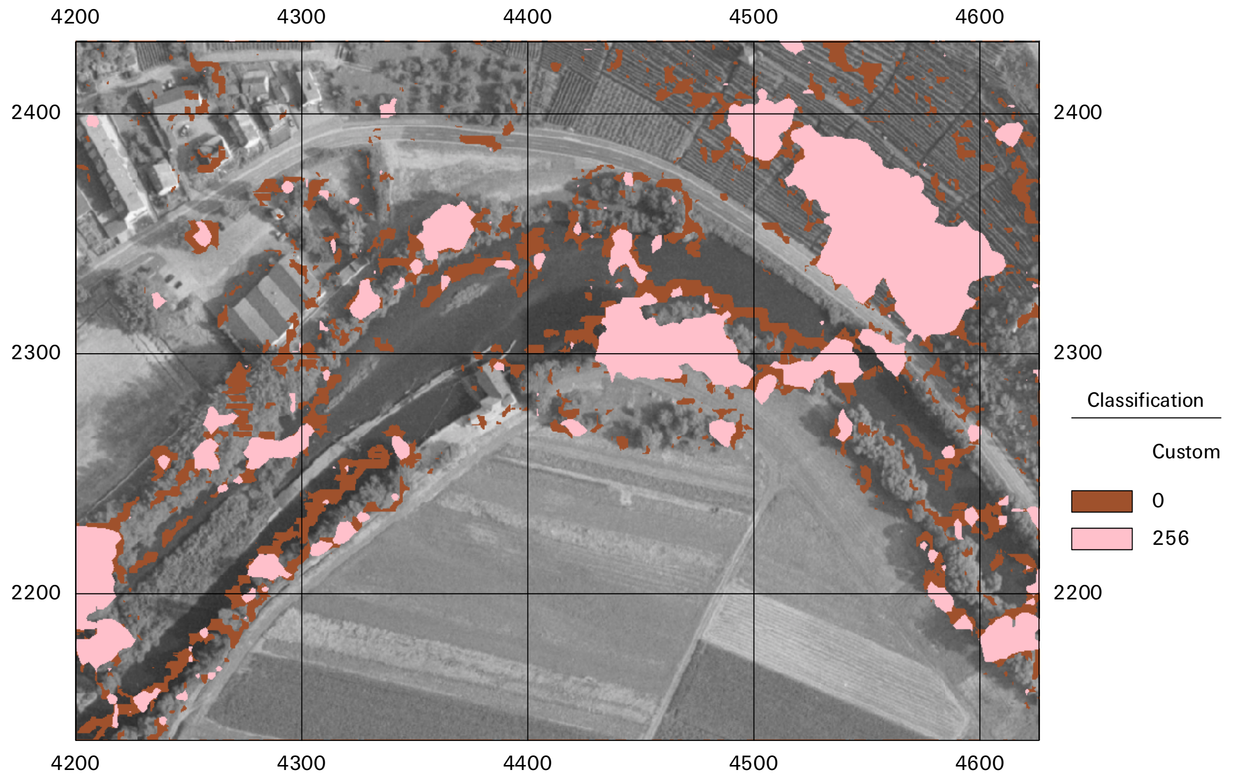

Figure 1, Example output from the FWM (best seen in colour)

The orthophoto then assists the user to check and edit the DEM. It is important to realize that the model does not alter the original DEM in any way; it merely highlights the areas that are likely to contain the highest residuals.

3.3 Testing the Failure Warning Model

The development of automated methods within digital photogrammetry allows the technology to be used by a wide range of new users, and hence a wide variety of potential applications. The FWM was therefore tested on a large number of areas visible within diverse sets of imagery and these results show that the FWM has performed consistently well. The tests were carried out by computing the residuals for each visible checkpoint. These residuals were then combined to create a r.m.s.e. for each of the three classifications identified by the FWM. The purpose of this was to determine if the points classified as "acceptable" did indeed have a **lower** r.m.s.e than the entire DEM. Conversely, if the areas highlighted by the FWM as "unreliable" (0 or 256) had a **higher** r.m.s.e than the entire DEM, this would indicate that the FWM was highlighting the correct points (i.e. those with the largest residuals). For brevity, the results from the tests on eight areas of one of the sets of imagery (1:13,000) are presented in Table 3.

	Area / r.m.s.e. value (m)							
FWM Category	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
"0"	3.91	2.76	1.90	0.39	1.00	2.89	1.94	1.99
Acceptable/OK	1.88	1.25	1.04	0.48	1.48	1.59	1.59	1.25
"256"	6.26	5.58	2.00	2.95	4.76	3.68	26.78	6.27
Default overall DEM	3.47	2.08	1.54	0.86	1.27	2.54	3.59	1.96

Table 3. Accuracy of classification using Failure Warning Model.

The results presented in Table 3 show that the FWM has worked well using the imagery selected for these tests. The points that are classified as "Acceptable" by the model consistently have a lower r.m.s.e than the overall model, suggesting that many of the points with the larger residuals have been filtered out. In four of the six areas, the points classified as "0" (points that the algorithm has interpolated over sudden elevation changes) had a higher r.m.s.e than the acceptable points. This was the case for all of the areas classified as "256" (areas susceptible to changes in the strategy parameters). The difference between the points classified as 256 and the rest of the points can be seen to be significant.

An excellent example of the successful usage of the FWM was provided by the 1:25,000 scale data set. This data set provided a unique case study because it perhaps represents the worst case scenario for automated DEM generation algorithms. The imagery is small scale and covers a mountain in Antarctica where there are large areas of clean snow (little gray level variation in the image) and a large elevation range. Both of these characteristics provide problems for area-based correlation techniques such as the one employed in the Ortho*MAX* algorithm. A quantitative analysis of the results can be seen in Table 4. The r.m.s.e. for the whole DEM generated using the default strategy parameters was 22.5m, indicating that some areas of the DEM contain significant errors. However, application of the Failure Warning Model has resulted in isolation of a significant portion of the points with the highest accuracy, as shown by the much better accuracy of the points classified as "Acceptable". The r.m.s.e. value of the points highlighted for editing is higher than that of the whole DEM, providing further indication that the correct set of points have been identified.

FWM Category	**r.m.s.e (m)**
"0"	26.7
Acceptable/OK	6.2
"256"	34.1
Default overall DEM	22.5

Table 4 Failure Warning Model Results for 1:25,000 scale data set

The distribution of the checkpoint residual errors can be seen in Figure 2. This graph illustrates the number of points within each of the ranges falling within each of the Failure Warning Model classifications. The results show that the majority of checkpoint residual errors fall in the range 0 to 5m for points classified as Acceptable/OK by the model, with a significant number in the range 5 to 10m. Although, there were still 107 points that had check point residuals greater than 10m (maximum 37.7m) that were classified as being OK by the model.

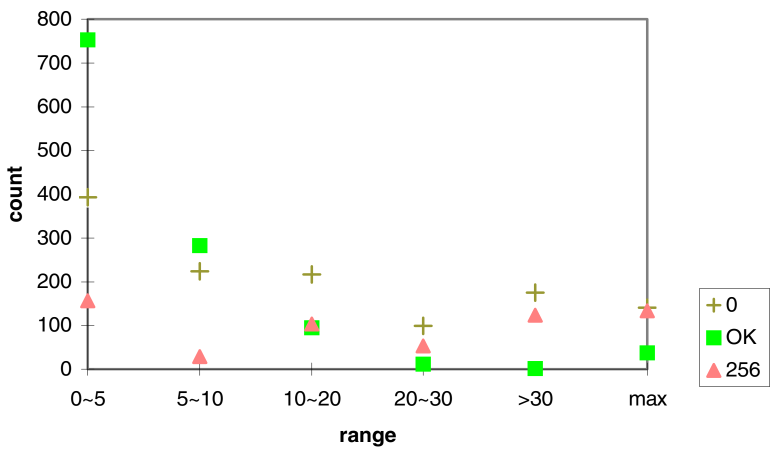

Figure 2 1:25,000 scale data set - check point distribution

Even more encouragingly, the distribution of the points classified as Acceptable/OK by the Failure Warning Model approximates to the normal distribution. This is important because it suggests that the Failure Warning Model is working satisfactorily. If we assume that the Failure Warning Model has isolated all gross errors and that systematic errors have been removed through proper calibration of the photogrammetric process, then the only errors that should remain are random errors. Error theory states that such random errors should possess the properties of the normal distribution. Examination of Figure 2 illustrates that the residuals for the points classified as "OK" are indeed normally distributed, providing further evidence of the success of the technique. However, the distribution of the other two groups is not ideal, as these groups include points that do have low residuals. Ideally, the Failure Warning Model should classify all low-residual points as "Acceptable/OK". Despite this, it can be seen that the model has highlighted the majority of points with high residuals, and the FWM has successfully isolated points containing the highest residuals (140.0m in the points classified as 0 and 133.5m in the points classified as 256).

3.4 Effectiveness of Failure warning model in other digital photogrammetric systems

The FWM was also tested on the Phodis TS DPS from Carl Zeiss, in order to demonstrate the universality of the approach. Clearly the technique would be of limited use if it could only be applied to one particular algorithm. The Phodis TS system uses the TopoSURF algorithm, which uses a correlation procedure to generate a large number of elevation points, from which a grid-type DEM is then derived. The Phodis TS software has two user definable strategy parameters, the Terrain Type parameter (flat, hilly or mountainous) and the Smoothing Factor (low, medium or high). The output from Phodis is an ASCII file containing the Cartesian co-ordinates of each point in the grid, followed by an estimate of the accuracy for each point. This estimate is defined on a scale from one to seven, one being the most accurate. This served as a basis for a comparison between the two packages and more importantly, to demonstrate the universality of the FWM approach.

Three areas of the 1:13,000 scale imagery were used in the tests, two with a 5 m grid spacing (Areas 1 and 2) and the other with a 10 m spacing. Area 1 covered mainly farmland with small, forested areas; Area 2 covered fields, trees, a steep slope, and a large residential area; and Area 3 covered rural and residential areas. A DEM was generated for each area with every combination of the two variable strategy parameters. Each DEM was then generated with the Ortho*MAX* DEM generation software using identical grid spacing.

The output data from the Phodis software was imported into the Imagine environment for comparison with the ERDAS data and testing of the FWM. The FWM had to be modified for the Phodis tests, since the software does not identify which points were interpolated during the DEM creation procedure and so only classifications of 256 or "Acceptable/OK" could be used. The input for each run of the FWM was therefore a DEM of the area generated using the default strategy parameters, a DEM of the area generated with one or both of the parameters changed, and an orthophoto of the area.

Area/r.m.s.e. (m)				
Phodis 1	**Phodis 2**	**Phodis 7**	**FWM Accept./OK**	**FWM "256"**
1.419m	3.618m	1.510m	1.301m	5.893m

Table 5. Phodis classification and FWM results model for Phodis data

Table 5 shows the average results for the three areas used to test the Phodis software. The results demonstrate that the FWM has performed significantly better than the Phodis classification system. This is shown by the fact that the points classified as unacceptable, (i.e., "256"), have a significantly higher r.m.s.e than the points classified as two or seven by the Phodis software. Also, the points classified as "Acceptable/OK" by the FWM have a lower r.m.s.e than the points classified as one by the Phodis software. Whilst the Phodis classification of two consistently had a higher r.m.s.e than the points classified as one, the points classified as seven proved to be somewhat less robust.

4 DISCUSSION

The research work has highlighted the many disadvantages of manual parameter optimization. Whilst significant improvements in the r.m.s.e. were achieved in some areas, this was only after extensive testing and regeneration of the same model. The large number of strategy parameters used in Ortho*MAX*, and other terrain extraction algorithms, means that testing every parameter combination is clearly impracticable. The tests have shown that although parameter settings can be critical, there is a wide variation in results for different areas. It could be argued that this merely supports the work of Zhang and Miller (1997) but it has been found that the relationship between area and accuracy is insufficiently strong to associate optimum parameter settings with particular area types. More significantly, it has been established that whilst parameter settings have a significant effect in certain areas, manipulation of the parameters has minimal effect in areas well suited to the matching algorithm. Furthermore, an improvement in accuracy in these areas is unlikely to be attained by manipulation of the strategy parameters.

The tests in this study were all carried out using imagery where checkpoint data was available. If checkpoint data is unavailable, optimization of the parameters becomes extremely difficult, as every model must then be checked manually. Even if check data is available, it was found that parameter optimization is difficult. This is a view shared by

Butler *et al.,* (1998) who demonstrated that improvements in internal results, such as matching success or the level of interpolation, are not always accompanied by an improvement in the accuracy of the DEM.

The Failure Warning Model provides an alternative approach to parameter optimization. Instead of attempting the lengthy process of optimization, the strategy parameters are used to identify areas where the software is likely to fail and identify areas where residuals are likely to be highest. Such information can be used as a guide when the DEM is checked, and is of value particularly to the novice user. Time spent during the editing phase is reduced to a minimum, thus increasing the profitability of a project. The FWM approach has been tested on a wide range of image scales and it therefore works in practice. It consistently highlights areas of DEMs with large residuals and results in unclassified areas having a lower r.m.s.e than that of the whole DEM. The approach has been tested also on the Phodis TS DEM generation software and proved to be successful, suggesting that the approach can be applied to other DPSs.

A number of other methodologies for quality control procedures of DEMs have been presented over recent years in the photogrammetric literature. Hannah (1981) suggested one approach that focused on a set of constraints on both the allowable slope and the allowable change in slope in local areas. However, this approach is not appropriate for all data sets because it relies on the assumption that sudden elevation changes in a DEM are indicative of potentially large errors. This may perhaps be the case in areas of open flat land such as the open fields in the 1:13,000 scale data set or the flume section of the 1:70 scale imagery used here, but it cannot be applied to residential, urban or forested areas. In these areas, sudden elevation changes are a key feature of the terrain. The algorithm presented by Hannah (1981) contains an error correction facility based upon a slope classification system, with points that fail being interpolated from surrounding elevation data. The application of such a technique to an urban environment would result in significant interpolation, the lowering of rooftops and the raising of street levels. It is interesting that this paper presents results from a rural area and not urban imagery and in essence, the approach is similar to that adopted by the Rejection Factor strategy parameter already embodied with the Ortho*MAX* software.

An alternative approach is that suggested by Li *et al.,* (1996). This technique uses orthophoto matching to identify residual parallax. Since orthophotos should contain no relief displacement, the presence of any parallax in the two images should indicate an elevation error. An iterative approach is described which automatically corrects the DEM until an allowable parallax threshold is reached and is usually convergent after two or three iterations. The results of several tests on the technique are presented in Li *et al.,* (1996), suggesting validity of the approach. Krupnik (1998) comments on this approach and suggests that problems may arise in areas with repetitive or homogenous texture, since most matching techniques fail in such areas. Instead, Krupnik (1998) proposes an *a priori* technique for the detection of erroneous areas. This system identifies areas that are difficult or impossible to match and suggests using alternative techniques (laser altimetry and radar interferometry are suggested) to obtain elevation estimates in areas where a photogrammetric approach is unsuitable.

The approach offered by the Failure Warning Model differs significantly from the approaches cited. Instead of attempting to correct and allow for problematic areas in a DEM, the areas are simply identified for interactive editing by the user. It performs an *a posteriori* analysis of the data generated as opposed to an *a priori* analysis of the imagery (as suggested by Krupnik, 1998). This is an important strength because this research has shown that it can be very difficult to predict regions in which the DEM generation algorithm will fail, suggesting that an *a priori* technique will always be difficult to implement. Until the unlikely situation arises when a "perfect" photogrammetric solution is developed, interactive editing and checking of the output will always be required. This is a view shared by Autometric, the developers of Ortho*MAX,* who suggest that it is an "inevitable fact that errors and blunders will occur in the automatic collection process, as they do in all ... measurement processes" (Grafton, 1999). The Failure Warning Model therefore offers the user much needed assistance for the editing and checking process, instead of trying to replace it.

Whilst there is an overlap between some of the technologies, for example the Failure Warning Model and the technique described by Hannah (1981), there is also the potential for integration of systems. The technique described by Li *et al.,* (1996) could easily be integrated with the Failure Warning Model such that an attempt is made to improve on the quality of the DEM, as well as reporting on potentially erroneous areas for interactive editing.

5 CONCLUSION

This paper has highlighted some of the problems and issues surrounding optimization of strategy parameters used in the automated generation of DEMs. It has shown that the parameter specification can be significant and that a manual optimization approach is lengthy and subject to a degree of variability. The Failure Warning Model (FWM) system has been described, which automatically identifies areas likely to contain inaccurate height estimates and results have been presented which prove the efficacy of the method. The output from the FWM is presented in an easy to understand graphical format, in the form of a classified monochrome orthophoto. Results can also be generated in color (Figure 1), which eases the identification of failed areas in gray-scale imagery. The FWM represents a completely new approach to identifying low accuracy areas of DEMs and makes full use of the actual DEM output from the DPS. By indicating the unreliable areas, the FWM also satisfies many of the concerns raised by others (e.g. Cooper, 1998; and Heipke, 1999) that current DPSs rarely assess the quality of the output. As it is a software-based assessment process, the FWM could easily be incorporated into an existing system, providing an internal and fully automated quality assessment procedure that is transparent to the user. The approach has proved successful on different software packages and for both close-range and aerial imagery of diverse subjects and scales.

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