

INTEGRATION AND FILTERING OF 3D SPATIAL DATA USING A SURFACE COMPARISON APPROACH

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ABSTRACT:

Combining a number of three-dimensional spatial data sets, which have been derived from different sources such as photogrammetry and more contemporary aerial and space-based remote sensing methods, demands that the integrity of the revised database be maintained. It is necessary to maintain or improve the combined data set's "size-to-information ratio". This problem is being tackled by treating both data sets as surface representations, and using a variation of least squares surface matching to permit the deviations of any point from the surface created by the other data set to be examined. The contributing data sets can suffer from systematic errors, which may be interpreted as anomalous regional position errors or height errors in a combined data-base, but surface comparison allows systematic error to be modelled within the matching process. A surface comparison approach also permits the search for objects among regionalised differences. Identifying objects within groups of differences indicates that the differences are real or erroneous, in which case the object can be retained in the combined data set. However, the first task is to ensure the perfect operation of the surface matching process which is subject to weak solutions caused by inhomogeneous point density and inappropriate surface textures. The work is being driven by a real application which arises in a project to form an accurate DTM for flood prediction purposes and subsequent disaster plan management studies. The task is to integrate a massive amount of height data from aerial photogrammetry with all existing ground surveyed points.

1. BACKGROUND: SPATIAL DATA AGGREGATION

The three dimensional spatial data required by interested and relevant agencies, such as the government and semi-government authorities involved in urban and non-urban planning and administration, can be gathered for them from a number of very diverse sources. These include, at the present time (being realistic) GPS ground surveys, aerial photogrammetric surveys (obtained both manually and automatically), aerial laser scanning (Lidar) coverage and traditional ground surveys methods. It is widely recognised that these multiple sources of 3D surface data differ in terms of their coverage, spatial density, accuracy and precision and the nature of the artefacts, objects and the features which they collect. The aerial photogrammetric surveys may be in the form of DEMs derived from automatic correlation in rural areas or as spot heights and contours derived from manual operations, especially in urban areas. Current or historical ground surveys can offer very different classes of output. Lidar and photogrammetry can have different sensitivities to vegetation and motor vehicles, and even buildings if that is in accordance with a photogrammetric operator's instructions. The contrast between photogrammetric collection of data on a regular grid, Lidar TINs, ground-based GPS, and traditional surveys (in which human decision makers are more likely to perceive and locate changes of grade and break-lines and linear features such as road centre-lines) can be vast. The differences in accuracy between ground-based surveys and aerial/space surveys may be in a ratio of 50:1.

When broad area coverage is needed for certain purposes - such as flood control, which is the problem of relevance in this study

- agencies can make maximum use of data sources by combining data sets derived from the different sources, into a single entity. The benefits of "multi-sensor integration" for "the fusion of DSMs of equal or different sources with equal or different spatial and temporal properties" (Schiewe, 2000) are well known, as is the fact that the combination of such data to provide an optimum set of ground point information is not as straight-forward as it may at first seem. This is particularly true when the data sources cover large extents but not necessarily identical areas, as they typically do with Lidar and photogrammetry. In the absence of other advice, any authority which disseminates or uses spatial information would normally use data sets from various sources by simply combining the (X,Y,Z) data together. However, such an agglomeration demands that the integrity of the revised database be maintained. The combined data set must be seamless and homogenous. That is, the data must be not have error sources which could cause the combined data to show either boundary effects nor display other differences due to the different errors. Moreover, it is not efficient to keep all points simply because they exist. It is necessary to check whether the new entity suffers from anomalies caused by sources of differences in the data sets. Furthermore, the combination data set's "size-to-information ratio" must be maintained or improved, and points cannot be retained simply because they occurred in one of the contributing data sets. As Ruiz (2000) points out with respect to the creation of a TIN model for Catalonia, "The model must be dynamic because it has to support insertion and deletion, the surface model should be refinable, algorithms have to be robust and data integrity must be preserved."

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The problem which we wish to address in this paper therefore is the means of creating a homogenous but filtered data set. That is, firstly sources of differences between the source files need to be examined, and secondly the combined file needs to be culled.

2. SHAPE MATCHING TO COMBINE AND FILTER DATA SETS - A PROPOSAL

The fundamental hypothesis behind the proposal which is being developed in this study, is that, by treating both data sets as surface representations, and using a variation of least squares surface shape matching to fit them together, various objectives of the spatial data merging problem can best be achieved. The aims of the process are:-

1. to detect any broad deviations between the surfaces, because they may indicate systematic error;
2. to detect any localised deviations between the surfaces, because they may indicate objects which have been detected by one system and not the other;
3. to detect any point deviations between the surfaces, because they may indicate individual data points whose retention is unnecessary.

Surface shape matching can be carried out by a number of techniques. However, with 2.5D surfaces as encountered in urban spatial information systems, least squares matching which minimises the surface separations is seen to be quite adequate and other approaches are unnecessarily complex. Mitchell and Chadwick (1999) have previously argued that the method is suited to matching of 2.5D surface comparison applications - when compared in particular with the Iterative Closest Point algorithm first proposed by Besl and McKay, 1992, and developed by various researchers since then. The least squares shape matching method has already seen use in spatial information studies by Jokinen and Haggrén, 1998, Postolov et al., 1999, McIntosh et al., 2000, Schenk et al., 2000, and Habib et al., 2001.

The concept of least squares shape matching for 2.5D surfaces is not complex, being in principle little different from the area-based image matching used to find the correspondence between image patches in digital photogrammetry. The method seeks to minimise the sum of the squares of the surface differences (rather than the noise in the individual observations, although this is of course a related measure). The required parameters are the parameters of the transformation which moves one surface coordinate system into coincidence with the other. While the coordinate systems are theoretically the same, it is the acceptance of the possibility of a small difference that permits interesting surface variations to be sought.

Like many least squares problems, the relevant equations need to be linearised and initial parameter values are generally needed (but see Habib et al., 2001). Fortunately, in the case of 2.5D spatial data comparison, the initial parameters are easy to estimate, being typically zero.

Details of algorithms and numerical implementation are given in a number of papers, which may be found via the references given in this paper. But despite the theoretical feasibility of least squares surface matching, in practice, numerical difficulties and precision problems can be encountered and these are discussed below following explanations of its usage in terms of the aggregation of spatial data.

3. THE ADVANTAGES OF SURFACE SHAPE MATCHING IN SPATIAL DATA MERGING

3.1 Differences across the entire surface: Systematic errors

The first advantage of using surface shape matching is to detect systematic errors. While none of the sources of data, whether from GPS, photogrammetry or Lidar is expected to suffer from any regular systematic error, in reality various errors can infiltrate the output: ground-based GPS surveys can incur a bias from satellite constellations at the time of survey, photogrammetry can suffer from errors in camera parameters including focal length error, Lidar can suffer from errors in the GPS control, calibration errors and problems with on-board sensor errors and gyro-control. Surface comparison by shape matching of can allow for systematic differences.

Systematic error can be detected by seeking patterns within the residuals. However, in a more sophisticated approach, it is also possible that a model of the patterns of systematic error can be integrated within the coordinate transformation which is chosen as the fundamental mathematical model of the least squares problem. Alternatively, mathematical shapes defining twists and other warping distortions can be used.

It is also noted that as an extension of this concept, (Buckley et al., 2002) argue that it is not necessary to control both the photogrammetry and Lidar if they can be fitted to each other using surface shape matching. However, our discussion here accepts, at least initially, that at the current time all commercial photogrammetry and Lidar data are controlled via GPS and/or ground control.

3.2 Differences across regions: Object identification

A second advantage of using surface shape matching across the surface defined by an entire spatial data set is that it permits outliers to be identified. Moreover, we can seek, by "blob" detection for example, from among the outliers, distinct parcels or regions of differences, which may in turn be identified as objects or features or attributes which have appeared in one type of data collection but not in another. These may be certain types of vegetation, moving objects such as motor vehicles, and new objects including buildings. More importantly, however, break-lines can be identifiable as they represent an attribute which is most importantly in the category of a attribute which is typically identified in some data sets (manual photogrammetry, and ground-based GPS survey or angle-and-distance surveys) and not in another. Items identified in this way may then need to be retained in the combined data set.

It is possible of course that the objects can be identified within the isolated "outlier" groups by appropriate analysis of the residuals. Such a capability is not part of this proposal, and is a separate issue, but it is important because an object which exists but cannot be identified may be incorrectly seen as due to errors and the points deleted. The crucial matter now however is that it is possible to group the surface differences, and that they are not always treated individually. The analysis therefore requires that any surface difference be sought as "regions" of differences, which could indicate new objects. These outliers can then be analysed for the existence of objects.

3.3 Point Differences: Filtering and blunder elimination

The third advantage of using surface shape matching is to examine the compliance of individual points with the overall

surface model. Points which are outliers deviate not only from one surface but from the combination, as surface-based comparison provides information on how well any point fits the entire combined data set. The alternative is to compare nearby points to each other, and not to see the overall picture. If a point deviates significantly - i.e. compared with the typical standard deviation - it may not be worth keeping, even if it is not a blunder, as it does not provide useful information. Thus the elimination of single outliers performs a filtering process.

When surface shape matching is used to correlate the surfaces, neither data set needs to be regarded as the correct or the control surface. It is not effective to accept that one point (probably from the "old" data) is correct, and that the new data point is being assessed. This may be true where one set of data is clearly superior, but when combining two sets of data from different remotely sensed sources, for example, one set must not necessarily be regarded as indispensable, superior or fixed. Treating the data sets as surfaces allows each surface to be given equal weight and influence, so both surfaces can be analysed equally and simultaneously.

The filtering of the data set clearly requires that points in either data set which are judged as erroneous must be rejected, and that useful points must not be rejected. More importantly however, some points in either data set which are not judged as erroneous but which add no new information, must nevertheless be rejected. In this process, therefore, it is important that all points be judged as to their contribution to the combined data set.

4. PROPOSAL SUMMARY

If the least squares problem is represented by the need to minimise the sum of the squares of the residuals V in the linearised matrix equation:

$$V = A \Delta + L \quad (1)$$

where Δ = vector of corrections to the required coordinate transformation parameters
 A = matrix of coefficients of the corrections to the required parameters
 L = vector of constant terms,

then we notice that our three aims are achieved by utilising the following characteristics of least squares estimation solutions:

1. systematic errors can be sought by introducing parameters describing the anticipated error patterns and are therefore sought via development of matrix A ;
2. object searching is carried out by analysing the outliers in the vector V ;
3. point filtering is carried out by analysing the elements of the vector V .

5. THE MATCHING ALGORITHM

The project development recognises that the first task is to ensure the validity and reliability of basic matching algorithms. The writers' experience with the matching concept means that they are aware of its weaknesses and difficulties; see Mitchell and Chadwick (1999). Shape matching is not robust, being ill-posed - being arguably an offshoot of image matching which is known to be ill-posed, (e.g. Heipke, 1996). Its strength in the

determination of the crucial shift parameters (which are most important in relating two spatial data sets positionally) will improve primarily with the existence of texture within the surfaces. Consequently, with the variety of surface textures which are encountered in real surfaces, the match does not always succeed, for the following considerations.

Despite the need for texture, algorithms based on minimising the vertical separation of 2.5D surfaces (or perhaps based on the normal distance) need to recognise that some surfaces have such features such as vertical surfaces (in the case of buildings and so on) and discontinuities (again typically associated with buildings) and the algorithm processing needs to be prepared for these eventualities.

Other considerations arise primarily from numerical issues, such as the need to interpolate corresponding points on one of the surfaces and from the need to estimate gradients. The interpolation error can be quite large because some interpolation distances in sparse TINs can be such that interpolation is simply unreasonable. The crucial point however is that the interpolation error - or the data point sparseness - needs to be estimated within the processing software in order that the dangers be made apparent. If the interpolation error can be estimated, it can at least be used in a weighting of the equations. Interpolation, and estimating the errors associated with it, is seen as particularly important when data is provided at varying spacings, when some regions of data are considerably sparser than others, and when point rejection is being undertaken.

It is also crucial to look at interpolation errors in order to get the difference values correct, and treating the data as surfaces is a means of interpolating among three or even more points. Studying interpolation and its errors can permit weights in the comparison process (especially to lower the weight on sparse areas) in surface matching.

The analysis depends on the classification of the outliers, a question which has been studied in surface matching by Pilgrim (1996) while it also must be recognised that finding outliers may be better pursued using least median of squares, (e.g. Xu and Li, 2000).

A matching program has been tested with both synthetic and real surface data sets, and the limits to the algorithm's robustness have been partly investigated. The program is using

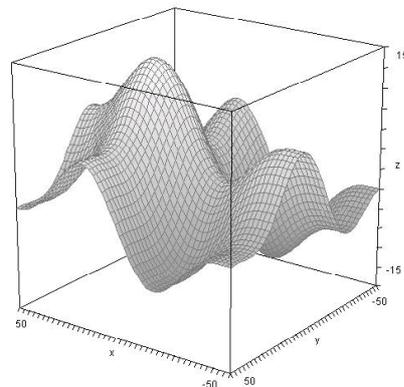


Figure 1. Surface plot of the mathematical function.

a 7-parameter conformal transformation to register the surfaces in the same coordinate system, i.e. match the surfaces. The parameters of the transformation are estimated in a least squares

solution, that minimises the normal distances of the points of one surface to the triangulated facets of the other surface. Another program that minimises the remaining differences along the Z axis has been previously created and used by Mitchell & Chadwick (1999). The authors intend to further studies on the comparison of the two algorithms (Schenk, 2000).

Synthetic data has been generated to test the program. The data consists of a patch of terrain 100m by 100m. The surface is generated by a function with the domain in X and Y from -50 to +50 and heights ranging approximately from -11.5 to +14. A plot of the function is shown in Figure 1.

The X and Y coordinates of the points are generated randomly, with the Z calculated from the X and Y coordinates. Two data sets representing the same surface were created in this manner. The first set was triangulated and used as a reference data set. The other set was transformed, that is the coordinates were shifted, rotated and scaled using a 7-parameter transformation.

The reference set was altered by eliminating the data in some patches of the set. A sample of the reference data used is shown in Figure 2. The aim was to emulate real situation matching where the reference data might be of high accuracy but patchy as if obtained by surveyors on foot, and to observe and analyse results obtained with such sets. The fact that the triangulation

occurred over the bare patches highlighted the necessity to weight the observation to minimise the interpolation errors. At equal density (r4, r5 and r6 contains 50 % of the points contained in r1, and cover 50 % of its area), reference surfaces with spread configuration such as set r4 were found to be the configuration for which the parameters used in the initial transformation were recovered the most closely. A configuration like the surface r5 generated the worst parameter recovery of all, for the reason that the configuration is unstable with relation to rotation with respect of the X and Y axes.

An important part of the research is to predict accuracy of matching process. The least square solution provides the user with statistical information on the matching of a cloud of points to a triangulated surface. It does not provide the accuracy of the matching of the points to the real surface.

Again an inspection of the results obtained by matching the data cloud to the reference surfaces shown revealed that reference surfaces configured as in r4 had the largest mean normal distance of the three configurations as well as the smallest standard deviation. The distances along the Z axis between the points of the transformed surface and the real surface were calculated in turn to show that the closest fit to the real surface (as opposed to the interpolated surface) when using a patchy reference surface was obtained when using reference data configured as in r4.

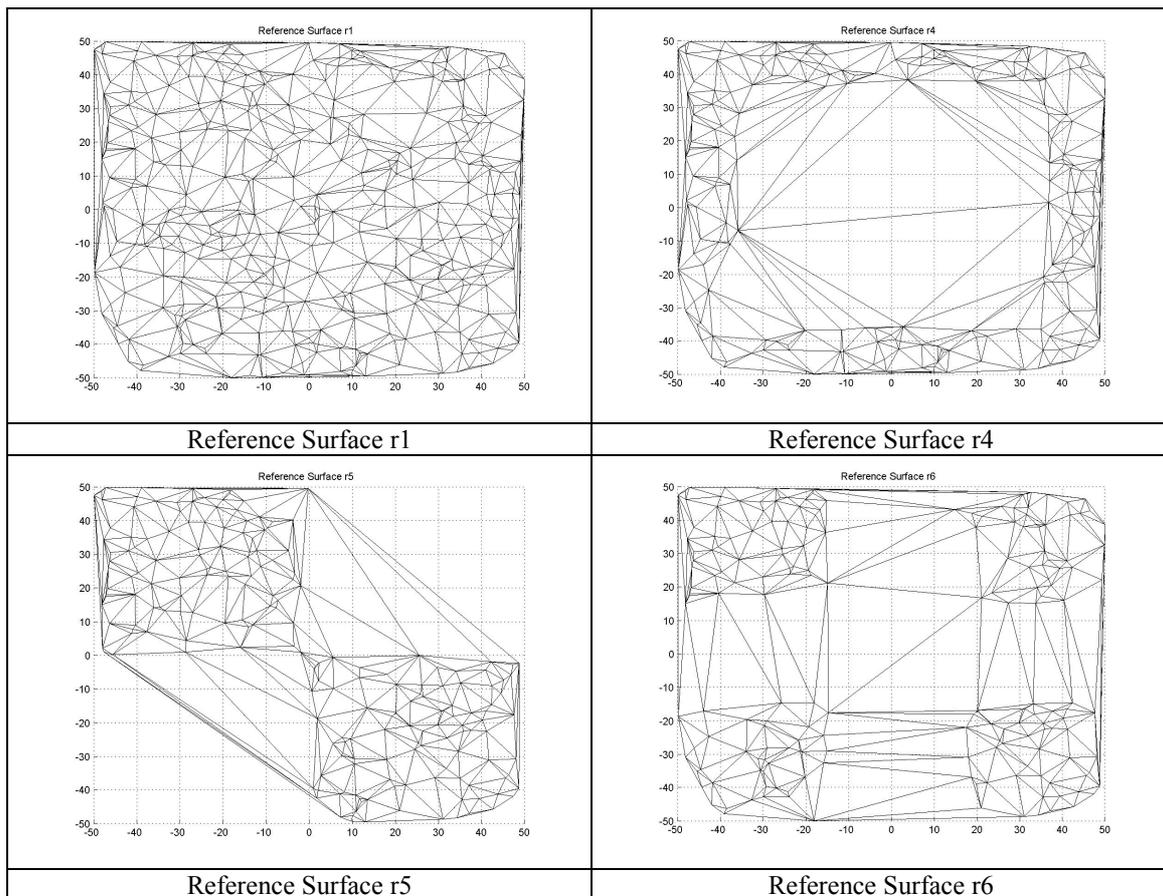


Figure 2. Test surfaces with sparse data.

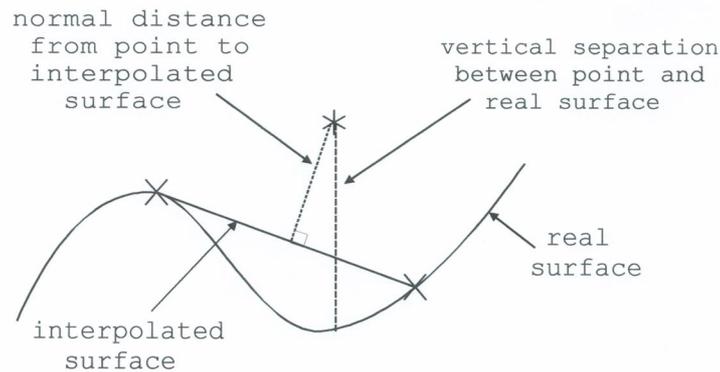


Figure 3. Normal distance to interpolated surface and vertical surface separation.

Prediction to optimise the fit could not in this case be based on the mean of the normal distances. Further research needs to be undertaken with different data distribution, different terrain characteristics (slope and wavelength), different data density and added noise.

6. APPLICATION

The work is being driven by a real application which arises in a project being carried out at Newcastle City Council. The task is to integrate a massive amount of height data from aerial photogrammetry with all existing ground surveyed points, and it thus provides an ideal test case for the implementation of the proposed procedure in detail. The city of Newcastle is on the east coast of Australia, approximately 150km north of Sydney. It has a major shipping port at the mouth of the Hunter River which drains the largely agricultural and pastoral Hunter Valley. Approximately 550,000 persons live and work in the Newcastle and Hunter Valley region which covers a total of 30,000 square km and is administered by 13 local government authorities. Newcastle City Council, the local government authority for the city and suburban region which covers 214 km², with 140,000 residents, plans to integrate all of its existing ground surveyed points with data from aerial photogrammetry, in order to form an accurate DTM for city flood prediction purposes and disaster plan management. However, initial attempts to combine the two data sets has shown that the increased size of the combined file does not necessarily equate to an increase in information, and that the data sets are not necessarily directly compatible, and it is proposed that the approach outlined here can contribute to a more efficient use of available data. Overall, it is argued that, when the two data sets are truly three-dimensional, the surface matching technique will permit a holistic approach to simultaneously determining both errors and true differences between the data sets.

7. CONCLUSIONS

It is crucial that the sources of weakness in surface shape matching be eliminated or overcome. However, it is argued that if this can be achieved then the residuals and functional models within the least squares procedure can be used to highlight matters of interest, in terms of single points, groups of points representing objects or systematic error patterns.

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