HKTM - AUTOMATIC REGISTRATION AND UPDATING OF SLOPE LASER SCANS

B. King[1], E. Matuk[1], K. Matuk[1], C.M. Gold[2], P. Kirk[3]

[1] Department of Land Surveying and Geo-Informatics
The Hong Kong Polytechnic University
Hung Hom, Kowloon, Hong Kong

[2]School of Computing
University of Glamorgan, Pontypridd, Wales, UK, CF37 1DL

[3]Geotechnical Engineering Office
Civil Engineering and Development Department
101 Princess Margaret Road, Kowloon, Hong Kong

E-mail: bruce.king@polyu.edu.hk

Abstract

HKTM is a system that has been developed to automatically register scans from terrestrial laser scans to create terrain models of natural and cut slopes. The system also can automatically update the terrain models in the case where there have been changes to the surface shape. The system makes use of spin images and cross correlation coefficients to automatically select correspondence points on overlapping scans. Graph structures are used to store the relationships between scans. Updating of the terrain model can be achieved by simply indicating on the terrain the approximate location of a new scan. To ensure accurate matching of scans a series of filters and checks is applied to the data before registration is performed.

1. Introduction

Once more than one laser scan is needed to describe a slope they have to be joined together (registered). If the slope changes it needs to be re-scanned and the terrain model updated. HKTM (Hong Kong Terrain Modelling) is a system that automatically performs the registration process without the use of special targets (thus removing the need to access the slope) and with a minimal amount of user input can update the terrain model when new scans are added.

At this stage of development, the registration itself is achieved via a standard three dimensional coordinate transformation. Future incarnations are anticipated to have more robust transformation strategies using, for example, iterative closest point algorithms (Besl and McKay, 1992; Campbell and Flynn, 2001; and Gruen and Akca, 2005). In order to perform the transformation, at least three points common to a pair of overlapping point clouds are needed to be identified. Many existing systems require the user to manually identify such common points. To automate this part of the procedure we have made use of spin images (Johnson and Herbert, 1997 and 1999) but techniques such as image skeletons (Gruen and Akca, 2005) and image processing techniques similar to those reported by Forkuo and King (2004) could also be applied. To ensure that those automatically selected points are correctly chosen, a series of statistical and geometric filters are applied.

The next section of this paper presents an introduction to spin images. Following this the filtering methodologies and results of initial testing of the system are presented.

2. Spin images

The concept of spin images was developed in Johnson (1997) and Johnson and Hebert (1999). A spin image represents the shape of a surface with respect to a specific point and is invariant with respect to viewing angle. Thus the spin image of the same point taken from point clouds with different orientation would be the same.

As spin images can be constructed from point cloud data, using them would provide a means to identify conjugate image points that would allow the registration of point clouds.

2.1 Constructing spin images

Spin images (Johnson, 1997) are simply transformations of the surface data; they are created by projecting 3-D points into 2-D images. Spin images are constructed at an *oriented point*. An oriented point, **O**, is defined by its 3D coordinates and surface normal, **n**, at that point. The relationship between **O** and surrounding points is established through the creation of a surface mesh typically by Delaunay triangulation and **n** is computed from the best fit plane, **P**, to the points connected to **O** by the mesh (Figure 1).

With respect to the oriented point and its surface normal each point on the surrounding point cloud is described by two coordinates: **α**, the perpendicular distance to the normal, and **β,** the (signed) distance above or below **O**, parallel to **n**. The coordinates for point **x** adjacent to **O** are computed by **(1)**.

$$(\alpha,\beta) = \left(\sqrt{\|x - O\|^2 - (n.(x - O))^2}, (n.(x - O)) \right) \tag{1}$$

Collecting (**α**,**β**) for points surrounding **O** characterises the shape of the surface at that point and constitutes the creation of a *spin map*, $\mathbf{S_0}$, which maps the 3D coordinates of the points into an orientation independent 2D set of coordinates. A spin map in itself doesn't allow the simple characterisation of the shape of surface around an oriented point as it would simply be a list of (**α**,**β**) values. The solution is to bin the (**α**,**β**) coordinates and present them in an image form. The pixels of the image represents bins of size (Δ**α**,Δ**β**) and the intensity of pixels how many (**α**,**β**) coordinates there are in the bin. The resulting image is called a *spin image* and an example is shown in Figure 2.

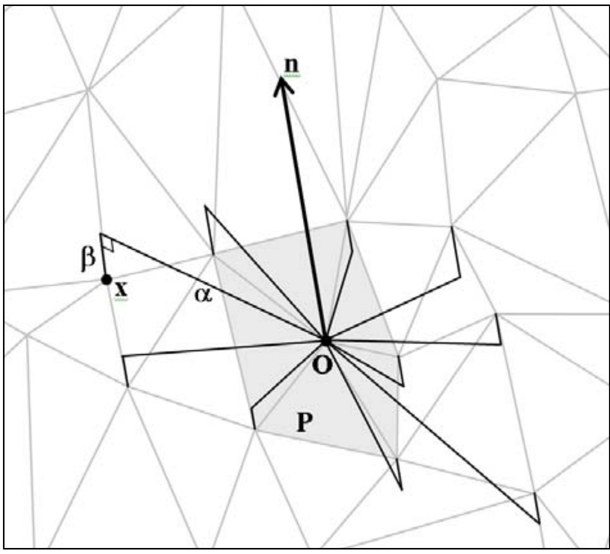

Figure 1. Spin map coordinates.

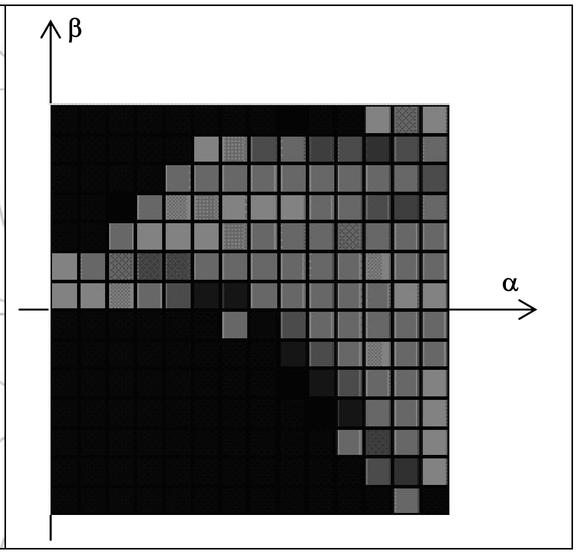

Figure 2. A spin image.

Parameters that must be considered when creating spin images are the bin size, the support distance (how far a point **x** can be from the oriented point to be included in the spin image), and the support angle (the maximum angle between **n** and the normal at **x)**. Details of these parameters can be found in Gold, Matuk and Matuk (2004).

2.2 Using spin images

Using spin images to find conjugate points on two points clouds simply requires that all the spin images be compared. This can be easily done with the normalised 2 dimensional correlation coefficient **R**. Given two spin images **P** and **Q** with **N** bins each, the linear correlation coefficient **R(P,Q)** is:

$$R(P,Q) = \frac{N\sum p_i q_i - \sum p_i \sum q_i}{\sqrt{(N\sum p_i^2 - (\sum p_i)^2)(N\sum q_i^2 - (\sum q_i)^2)}} \quad \textbf{(2)}$$

where **R** is between -1 (anti-correlated) and 1 (completely correlated).

Johnson reports there are some statistical problems related to using **R** by itself and proposes the similarity value given in **(3)** to overcome them. His argument is that the reliability of **R** depends on the number of cells in the spin image that contain data and so the *similarity measure*, **C**, is weighted to reflect this. When using Johnson's measure we found that the matching of correspondence points was not reliable.

$$C(P,Q) = (\operatorname{atanh}(R(P,Q)))^2 - \lambda \frac{1}{(N-3)} \quad \textbf{(3)}$$

Re-thinking the meaning of using spin images lead us to conclude that the spin-image cells that did not have any data were just as significant as those that contained data as the empty cells characterise the shape of the surface just as importantly as cells with data. Thus the similarity measure used in HKTM has the weighting component removed as shown in **(4)**. This measure was found to be much more robust in identifying conjugate points.

$$C(P,Q) = (\operatorname{atanh}(R(P,Q)))^2 \quad \textbf{(4)}$$

3. Mesh filtering and point importance

Laser scan point clouds typically contain a large number of points so, in order to reduce the time spent computing **C** for all points, only a subset of all available points are used as possible conjugate points. Thus it is important to make sure that selected points are meaningful and could be found on overlapping scans. Two concepts, importance and filtering, are used to generate meaningful points.

As much of the processing involves the Delaunay generated mesh of the surface points, some of the filtering of meaningless points can be achieved by analysis of the mesh triangles. A filter to remove long, narrow triangles (small base:height ratios) was found to be useful in removing points on the boundary of the mesh and noise from the scanner. First a histogram of the ratio of altitude to longest side for all triangles is built (Figure 3). The mean value is then used as a cut-off to select points whose triangles are well formed. Points with base:height less than the mean are excluded from further consideration.

An important factor in describing the shape of a surface is its slope and how it changes from point to point. A rapidly changing surface slope is considered to be a desirable property as it would produce distinct spin images. Change in slope was characterised by the cosine of the angle between surface normal at each point. The bigger the angle, the lower cosine value, the more important is the point. Thus, an *importance* was assigned based this cosine value. Those points remaining after the histogram filtering were ranked by the importance value with lower numbers having higher rank. The user can then specify how many of these points are to be used in the remainder of the matching processes.

These two filters alone do not guarantee that, after the matching of similarity measures, the paired points have the same location on the two point clouds. Further outliers were identified and removed from the list by the application of a geometric filter. The 3D distances between a point and all other points on both meshes and the differences between these distances are computed. Those points that satisfy a threshold for the distance differences are considered to be geometrically correct matches.

4. A transformation strategy

The following sections present a methodology that was implemented to automatically filter and match conjugate points which were then used as control points for the transformation of one point cloud onto another. The process can be summarised as:

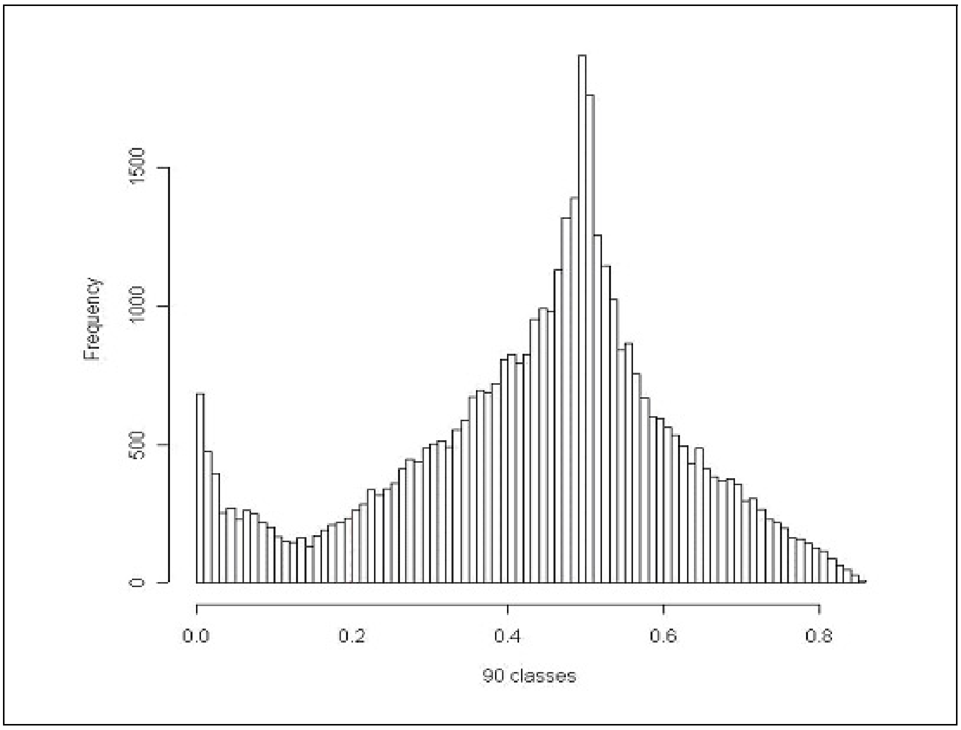

Figure 3. Triangle elimination histogram

1. open two point clouds (one is the primary point cloud, **P**, the other is the secondary point cloud, **S**) and create surface meshes by Delauny triangulation;
2. filter the points for both meshes as mentioned in the previous section;
3. create spin images $\mathbf{p_j}$ and $\mathbf{s_i}$ for all identified points on **P** and **S**;
4. compute the similarity measure, $\mathbf{C_i}$, between all $\mathbf{s_i}$ and all $\mathbf{p_j}$
5. create a preliminary list of candidates for conjugate points based on the point pairs with the largest $\mathbf{C_i}$;
6. apply the geometric filter for all conjugate point pairs.

At the end of this procedure, a robust set of conjugate points is obtained and the registration done as outlined in the following section. After registration a final filtering is done of points in the overlap area of the secondary point cloud. The filtering is achieved through the application of a spherical search, the radius of which is set as a user editable parameter in the HKTM system. Before each point on **S** is added to the terrain model the distance between it and points of the **P** scan are compared to the search radius. If the distance is greater than the search radius then it is added if not it is ignored.

4.1 Transformation of scans

A three dimensional conformal transformation of one point cloud, **S**, into the coordinate system of the other, **P**, requires a minimum of conjugate points. As the transformation equations are non-linear, initial estimates for the transformation parameters (three rotations and three translations – scale can be assumed to be equal for the two point clouds) are required and an iterated least squares solution computed. The method proposed by Dewitt (1996) was used. When more than three correspondence points are available, the altitude from the longest side of the all possible triangles created from selected points is computed and the triangle with the largest altitude is chosen. During least squares iteration the RMS error between the two data sets is computed and used for detection of conjugate points to be excluded from the computation.

5. Testing the methodology

Initial testing of the methodology as implemented in the HKTM system was done with the dataset Bunny. This was one of the datasets used by Johnson (1997) in the original development of the spin image concept.

Bunny consists of two scans of a toy rabbit with the toy rotated 45 degrees clockwise between scans (Figure 4). Each scan consists of just over 40,000 points with an average spacing of 0.7mm.

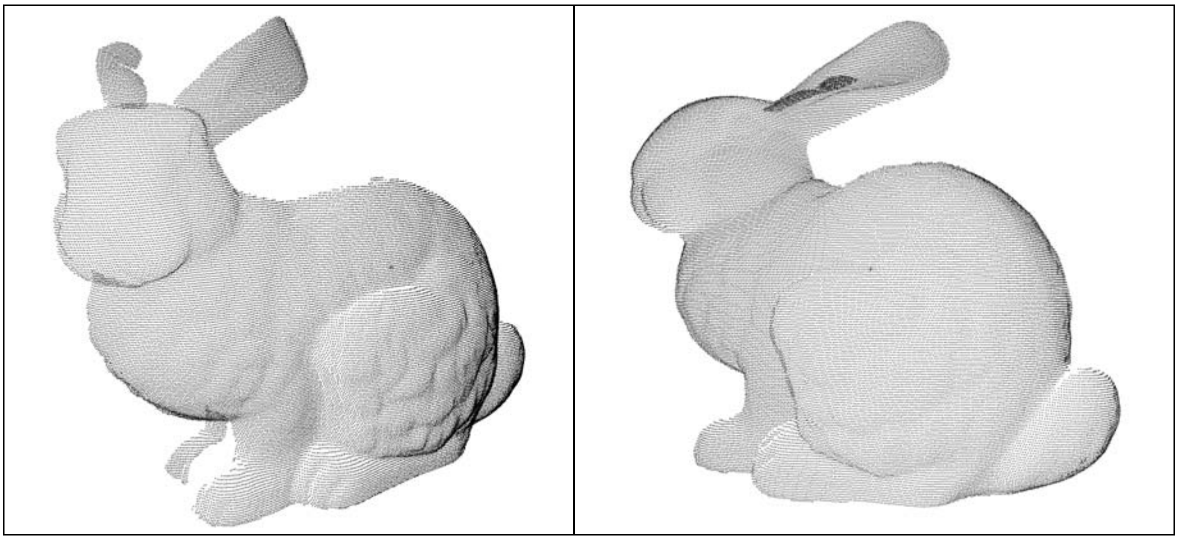

Figure 4. Bunny scans. Zero rotation (Bunny00) on the left left and 45 degree rotation (Bunny45) on the right.

A second dataset, Tiles, more representative of natural terrain was a dump of old flooring tiles scanned with a CYRAX 2500 terrestrial laser scanner. The dump was about 10 metres long, 1.5 metres high and 3 metres deep. The back and right side of the dump were constrained by walls. Because the surface was extremely rough it was draped with brattice cloth (Figures 5 and 6) to create a more natural surface. Ten different scans with nominal resolution of 10mm at the centre of the scan area were made from three different locations but testing was done with just two pairs of them. Initially scans 9 and 10 (Figure 5) from the same location and the scanner rotated were used as 100% of Tiles9 (125,000 points) is contained within Tiles10 ensuring that conjugate points could be found. The test was then repeated using scans with less overlap - Tiles 6 and 7 (Figure 6) from the same location and the scanner rotated. The overlap between these two point clouds was about 70%, 93,000 points. The walls and floor were removed from all point clouds prior to processing.

Each pair of point clouds were registered by both HKTM and Cyclone, the point cloud software that is part of the CYRAX system. Cyclone uses a semi-automated approach to undertake the registration. Firstly a minimum of three conjugate points are identified by an operator picking them from the two point clouds, and secondly an ICP algorithm is run to perform the registration. The internal accuracy of each registration by both software systems are given by their respective RMS errors and are shown in boarders of each table. Bunny45 was registered to Bunny00, Tiles9 to Tiles10 and Tiles6 to Tiles7.

The external accuracy of the HKTM registrations was quantified by the RMS coordinate differences (in the body of each table) between the registered point clouds produced by each program. That is, the RMS errors between the Cyclone and HKTM transformed coordinates of Bunny45, Tiles9 and Tiles6 scans. To see what effect the number of points used to compute the transformation had on the process, the registrations were computed with different sub-sample percentages for Cyclone and different oriented point numbers for HKTM. The results of each test are presented in Tables 1, 2 and 3 for Bunny, Tiles 9 and 10 and Tiles 6 and 7 respectively.

6. Results

The Bunny dataset showed that the external error between the relatively simple 3D conformal transformation used by HKTM and the ICP transformation used by Cyclone are all less than half of the scanning resolution. The internal accuracy of HKTM is, across the board, higher than for Cyclone. It should be remembered though that the number of conjugate points is taken from the list of importance values and the final number of points used in the HKTM registration is much smaller than that used by Cyclone's ICP algorithm. Thus the number of points used to generate the internal accuracy is much less than the number used in Cyclone.

Compared to Bunny the Tiles data sets are very different. The scale of the object is much larger, the point spacing is lower and the surface more irregular. The internal accuracy produced by HKTM for both data sets were similar at around 2 times the scan resolution, but both are significantly larger than the internal accuracy produced by Cyclone. This was attributed to the difference between using ICP and a simple 3D conformal transformation. The ICP process used by Cyclone will continually refine the matching points whereas HKTM will only refine the orientation parameters based on the correspondence points.

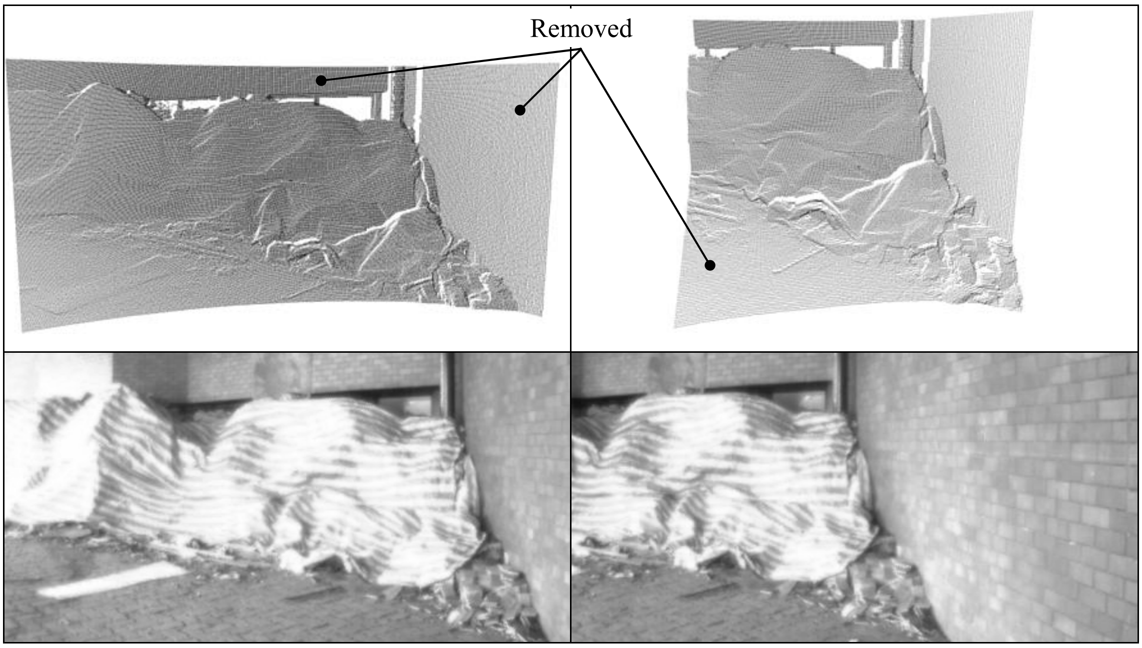

Figure 5. Tiles 10 (left) and Tiles 9 (right)

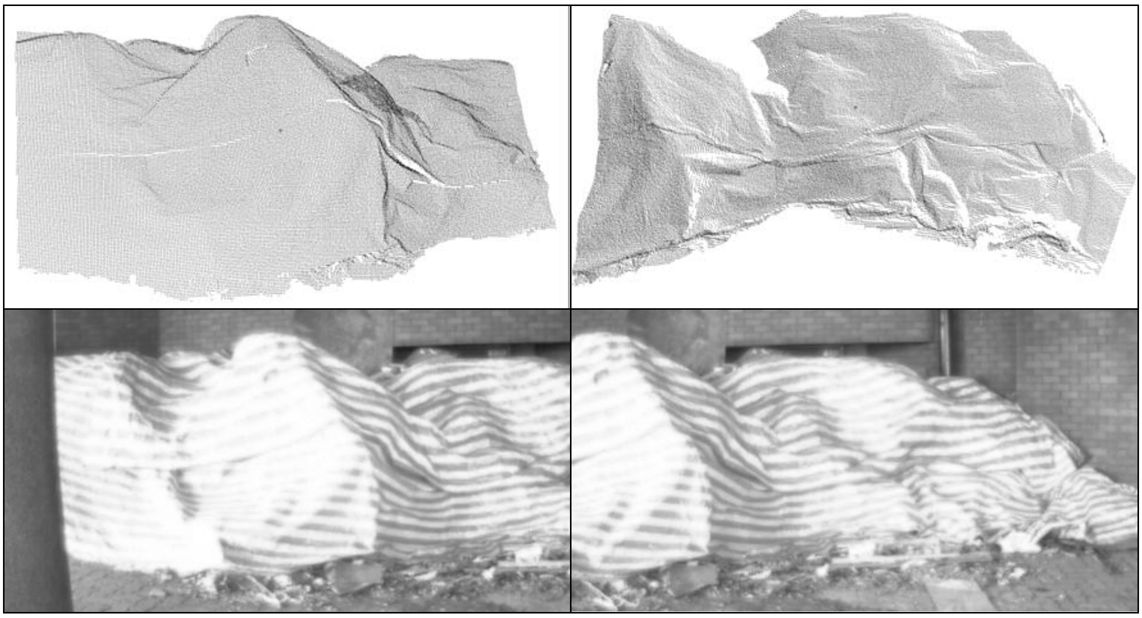

Figure 6. Tiles 7 (left) and Tiles 6 (right)

Despite such poor internal results the external results were all within half of the scan resolution. This reinforces the result from Bunny and our conclusion that the automatic correspondence point methodology is not fundamentally flawed. It is comforting too that there was no significant change in external accuracy as the Cyclone subsampling was reduced. This evidence all indicate that the use in HKTM of a more sophisticated registration algorithm such as ICP is worthwhile investigating. Details of the results of this testing can be found in Matuk et al (2006).

7. Terrain model updating

Once a terrain model is created the need to update it arises. One feature of HKTM that allows this to be easily done is the tracking of registration information between all laser scans by a graph structure. In order to update a terrain model all that's required is to indicate where on the existing model the new scan is located. This allows HKTM to identify the existing neighbouring scans and the registration linkages between them.

Updating of the terrain model is achieved in a way that is identical to its initial creation. The existing terrain model is read into the HKTM system, the pairwise matching of the new scan to the underlying scan is performed as described above and the graph structure updated with the new orientation information. A two dimensional filtering is then done to ensure the data relating to the superseded point cloud is removed. Finally, the new terrain model is created.

8. Conclusions

The use of spin images to automatically generate correspondence points for the registration of laser scanner point clouds has been implemented in the HKTM system. Graph structures and a series of geometric and statistical filters are used to ensure the integrity of the terrain models created from individual scans. The HKTM system has been tested with both simple and complex point clouds and against an industry standard software system and was found to perform reliably given the lack of sophistication of the registration algorithm. Based on the findings of this research further development of HKTM will be on several fronts: the first is to use a more sophisticated registration algorithm such as ICP, the second is to investigate alternative approximation estimation and the third to assess the impact of very large datasets on the stability of the system.

9. Acknowledgments

The work described in this paper was substantially supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region (Project No: PolyU 5161/03E).

10. References

Besl, P.J. and McKay, N.D., 1992. "A method for registration of 3D shapes". *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 14(2):239-256.

Campbell, R.J. and Flynn, P.J., 2001. "A survey of free-form object representation and recognition techniques". *Computer Vision and image Understanding*, 81(2):166-210.

Dewitt, B.A., 1996. "Initial approximations for the three-dimensional conformal transformation". *Photogrammetric Engineering and Remote Sensing,* 62(1):79-83

Forkuo, E.K. and King, B., 2004. "Automatic fusion of photogrammetric imagery and laser scanner point clouds". *International Archives of Photogrammetry and Remote Sensing*, XXXV(B4):921-926.

Gold, C.M., Matuk, E. and Matuk, K. 2004. "Terrain reconstruction from ground-based laser data". *4th International Symposium on Mobile Mapping Technology*, Kunming, China, 29-31 March 2004.

Gruen, A. and Akca, D., 2005. "Least squares 3D surface and curve matching". *ISPRS Journal of Photogrammetry and Remote Sensing*, 59(2005):151-174.

Johnson, A.E., 1997. *Spin images: A Representation for 3-D Surface Matching.* PhD Thesis, Carnegie Mellon University Pittsburgh, Pennsylvania.

Johnson, A.E. and Hebert, M., 1999. Using spin images for efficient object recognition in cluttered 3D scenes. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 21(5):433-449.

Matuk, E., King, B., Matuk, K., Gold, C.M. and Kirk, P., 2006. "A method for the automatic registration of terrestrial laser scanner point clouds". *Journal of Geospatial Engineering.* Accepted for publication.