A method for the automatic registration of terrestrial laser scanner point clouds

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Abstract

As part of a system being developed to manage large terrain reconstructions from laser scanner point clouds, a methodology based on the use of spin images to automatically pair-wise register point clouds has been implemented. Individual point clouds are meshed via Delauny triangulation, the mesh is filtered to exclude undesirable points from further processing, importance values are determined to identify salient surface features, spin images are extracted from each point cloud and then conjugate points established by image correlation, similarity measures and geometric filtering. The registration is implemented as a simple 3D conformal transformation. Initial testing on three datasets was done with the developed system and the results compared to those produced by the Cyclone point cloud software. The results indicate that the developed methodology is reliable but could be improved with a more sophisticated orientation strategy such as that provided by an iterative closest point algorithm.

1. Introduction

The terrestrial laser scanning of large sections of terrain require that the scanner be set up in various locations and the individual scans be registered together. In software systems delivered with terrestrial laser scanners, the registration process is typically a two step process - firstly a minimum of three points common to a pair of overlapping scans are identified and secondly the registration is typically performed by an iterative closest point type algorithm. The selection of points may either by achieved via the use of automatically recognised targets within each scan or by an operator identifying conjugate points in the two point clouds. The former makes the registration process all-but automatic but it may not be feasible to place such targets in every scan being collected. When reconstructing extensive terrain models that do not contain such special targets, the manual process of selecting conjugate points can be very time consuming making automation of the process a necessity.

Various methods have been developed to undertake the transformation (registration) process. The simplest is a 3-dimensional conformal transformation of one point cloud onto the other. The limitation of this is that it assumes there is an exact correspondence between the two sets of points, something that is rarely the case. The basis for many of the more accurate transformation algorithms is the Iterative Closest Point (ICP) algorithm proposed by Besl and McKay (1992) with variations being developed to cater for the characteristics of different types of datasets. Overview of the various implementations of ICP-based algorithms is given by Campbell and Flynn (2001) and Gruen and Akca (2005).

Work on the automatic selection of conjugate points has been in progress for several years. As reported in Gruen and Akca (2005), methods that have been employed include the use of 3D skeletons, Fourier transformations and Hough transformations. Image processing techniques similar to those reported by Forkuo and King (2004) used to register photographic images to point clouds may also be applied.

Spin images (Johnson and Herbert, 1997 and 1999) provide a useful tool for the process of selecting conjugate points. Spin images have the characteristic that they are rotationally invariant, and so are ideal for the application to point clouds of the same feature obtained from different locations. Due to this unique characteristic, the application of spin images to the automatic registration of terrestrial laser scanner point clouds was investigated as part of the development of a software system to manage large point cloud datasets for the reconstruction and updating of terrain models of Hong Kong slopes.

This paper presents the approach developed for a terrain reconstruction and management system (HKTM). The basic concepts of spin images are explained, the parameters for filtering and the determination of conjugate points outlined and the results of testing with several data sets are presented. The results of this experiment will be used to decide on the direction of further development of the HKTM system.

2. Spin images

The power of the human visual system to assess the similarity between areas surrounding conjugate point pairs between two point clouds a relatively easy task, even if there are large differences in the view angle of the laser scanner that generated the point cloud. Doing this automatically requires that the similarity of areas around conjugate points, irrespective of the view angle of laser scanner can be quantified. An effective measure of similarity is based on the concept of spin images 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).

An oriented point defines a 5 degrees of freedom basis (**O**,**n**) with the two coordinates of the basis being **α**, the perpendicular distance to the normal, and **β**, the (signed) distance above or below **O**, parallel to **n**. For a point **x** adjacent to **O**, the parameters of the **(O,n)** basis are computed by **(1)**.

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

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.

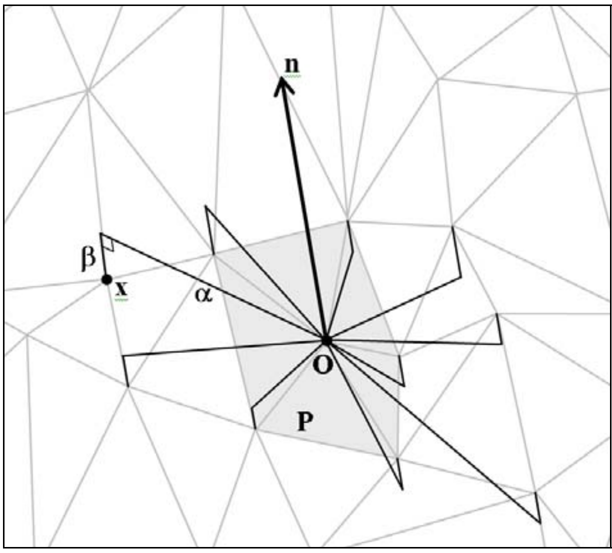

Figure 1. An oriented point basis.

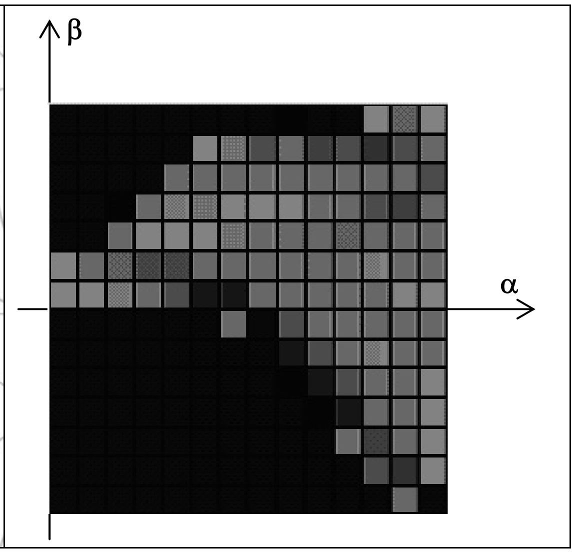

Figure 2. A spin image.

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

If we have two point clouds and we create spin images for all oriented points, then the similarity between the oriented points of the two point clouds can be assessed by comparing their spin images. The standard way of comparing linearly related images is the normalized *linear correlation coefficient*, **R**. Given two spin images **P** and **Q** with **N** bins each, the linear correlation coefficient **R(P,Q)** is:

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

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

In order to overcome some statistical problems related to using **R** by itself, Johnson uses the similarity value given in (3). 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. 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 useful in identifying matching correspondence points.

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

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

3. Mesh filtering and point importance

Laser scan point clouds typically contain a large number of points so, in order to reduce the computation time, only a subset of all available points are used as possible oriented 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 oriented 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. Some of the triangles created by the triangulation process must be removed because they do not accurately represent the surface. These include triangles between points on the boundary of the object as well as noise along the line sight of the scanner created by scanner noise. Usually both types of triangles are long and thin (small base:height ratios). To detect and filter out those undesirable triangles 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 in selecting candidates for orientated points.

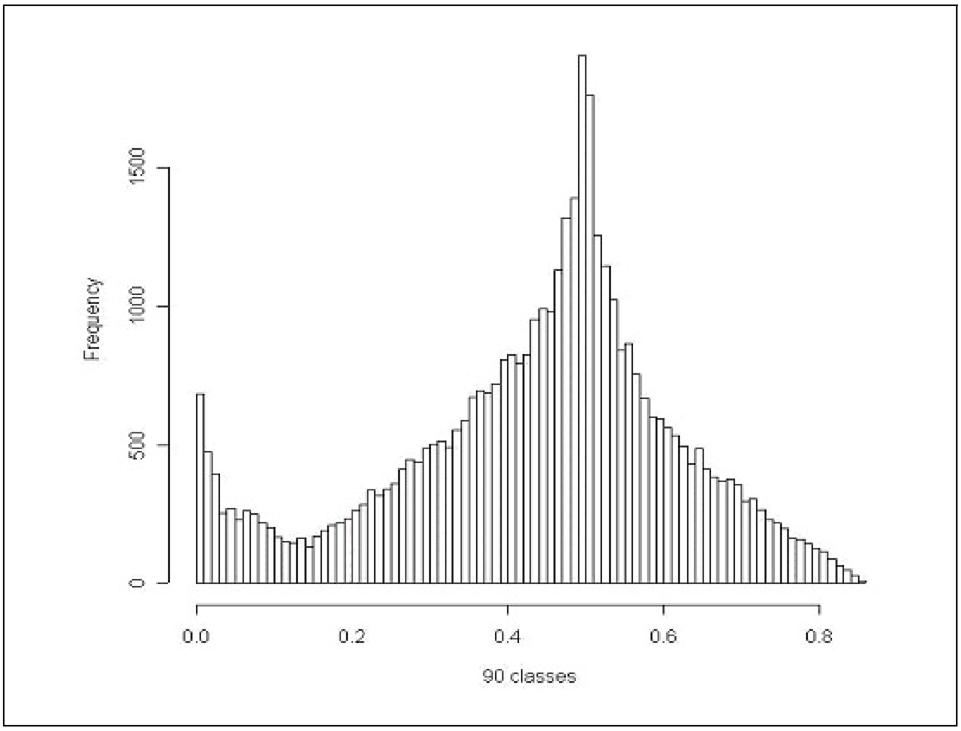

Figure 3. Triangle elimination histogram

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 compared to those created by a slowly changing surface slope. 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 are the *oriented points* mentioned earlier.

From this set of points, *correspondence points* are to be found. This is initially done via computation of correlation coefficients and similarity measures. These alone do not guarantee that the paired points have the same location on the two point clouds. A geometric filter is used to refine the list of correspondence points. The 3D distances between a correspondence point and all other correspondence points on both meshes and then 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 oriented points (called *correspondence points*) which were then used as control points for the transformation of one point cloud onto another. The process can be summarised as:

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 $\mathbf{c_j}$ and $\mathbf{s_i}$ for all oriented points on **C** and **S**;
4. compute the similarity measure, $\mathbf{C_i}$, between all $\mathbf{s_i}$ and all $\mathbf{c_j}$
5. create a preliminary list of candidates for correspondence points based on the point pairs with the largest $\mathbf{R_i}$;
6. apply the geometric filter for all correspondence point pairs.

At the end of this procedure, a robust set of correspondence points is obtained.

4.1 Transformation of scans

Assuming that the scales of the two point clouds are the same (valid for laser scanner point clouds), single correspondences cannot be used to compute the parameters necessary to transform the mesh **S** into the coordinate system of mesh **C.** In our method at least three correspondence points in both systems are required. A plausible 3D rigid transformation **T** from model to scene is calculated from each group ($\mathbf{c_i}$, $\mathbf{s_i}$) of correspondences by minimizing:

$$\mathbf{E_T} = \sum \left\| \mathbf{s_i} - \mathbf{T}(\mathbf{m_i}) \right\|^2 \qquad \textbf{(4)}$$

Initial approximation of the transformation parameters (three rotations – omega, phi, kappa and three translations – in x, y, z) has to be estimated. To do so, the method proposed by Dewitt (1996) has been 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 which should be excluded from the adjustment.

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.

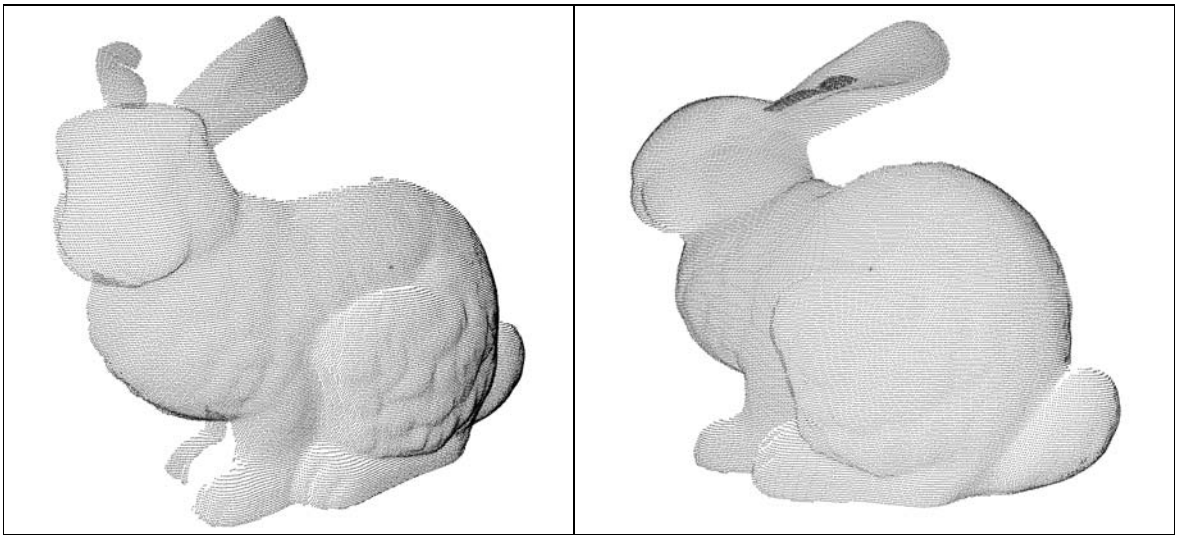

Figure 4. Bunny scans. Zero rotation (Bunny00) on the left left and 45 degree rotation (Bunny45) on the right.

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.

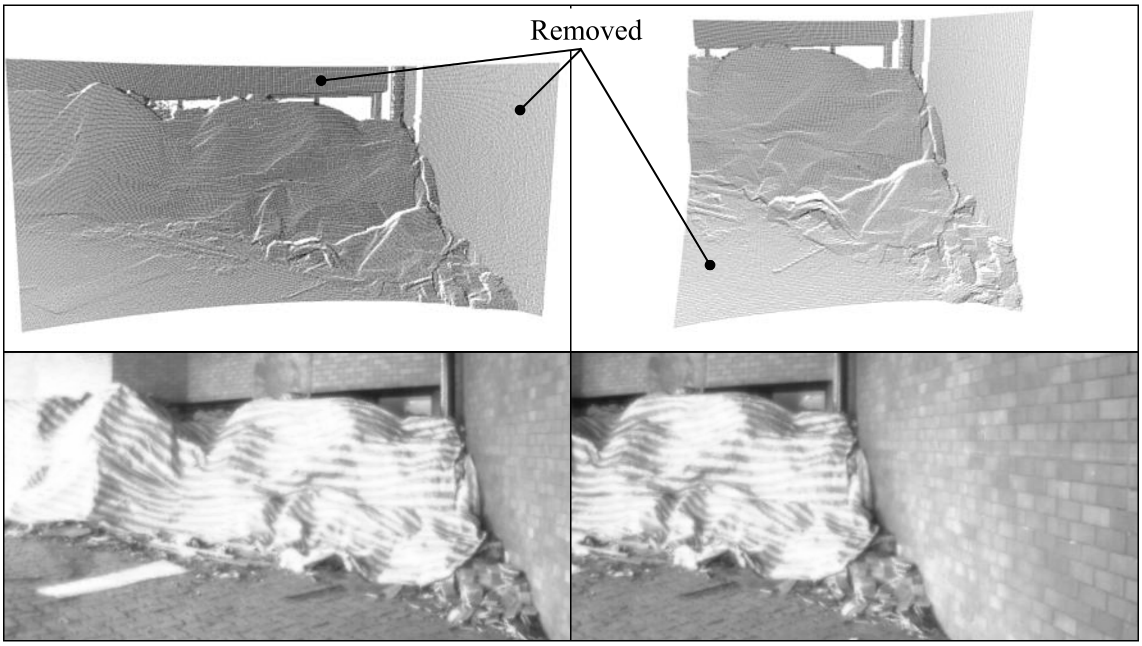

Figure 5. Tiles 10 (left) and Tiles 9 (right)

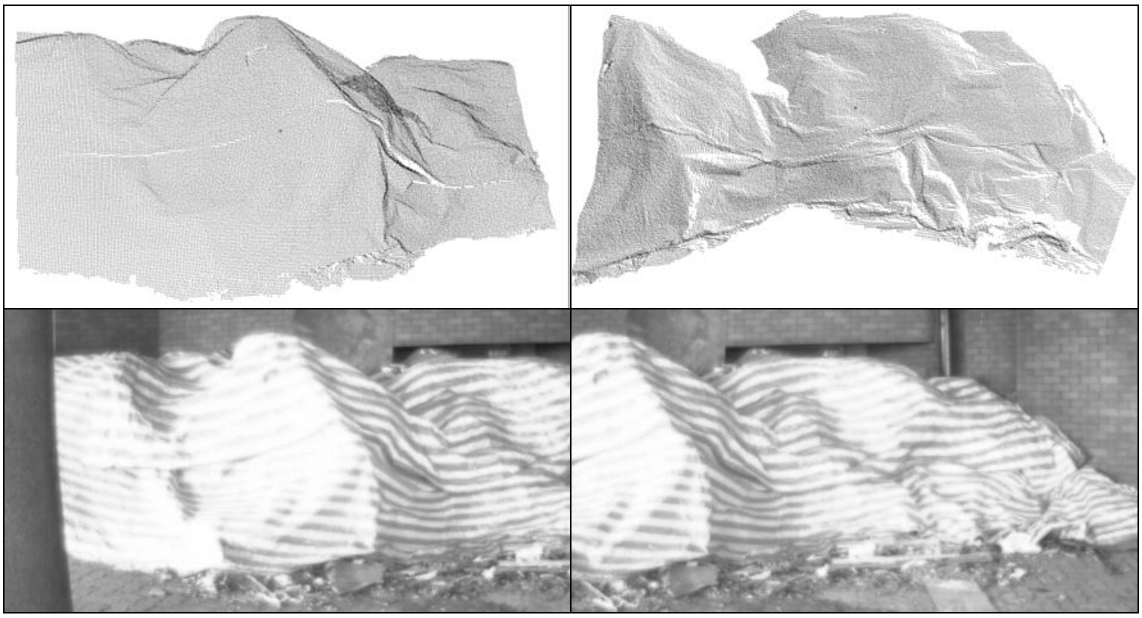

Figure 6. Tiles 7 (left) and Tiles 6 (right)

6. Results

The Bunny dataset shows 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 oriented points is taken from the list of importance values and the final number of points used in the HKTM registration is the number of correspondence points. Thus the number of points used to generate the internal accuracy is much less than the number used in Cyclone. One interesting result is generated from the 800 oriented point HKTM data set. For some unexplained reason, only 3 correspondence points were selected to be used as oriented points even though they came from the same list as the 3,000 and 600 oriented point data sets. Logic says that there should have been between 19 and 27 correspondence points found. Neglecting this unusual result it can be seen that as the number of correspondence points decreases so does the accuracy of the HKTM orientation. The results of Bunny were very encouraging but we suspected it was more to do with the density of the data and the shape of the object.

Table 1. Results for Bunny
OP = oriented points, CP = corresponding points

HKTM → Res: 0.7mm **↓ Cyclone**	OP: 4500 CP: 55 RMS: 0.5mm Iterations: 5	OP: 3000 CP: 27 RMS: 0.4mm Iterations: 4	OP: 800 CP: 3 RMS: 0.04mm Iterations: 2	OP: 600 CP: 19 RMS: 0.7mm Iterations: 5
Subsample: 90% RMS: 1.6mm Iterations: 17	RMS: 0.1mm	RMS: 0.2mm	RMS: 0.1mm	RMS: 0.3mm
Subsample: 50% RMS: 1.6mm Iterations: 16	RMS: 0.1mm	RMS: 0.2mm	RMS: 0.2mm	RMS: 0.3mm
Subsample: 30% RMS: 1.7mm Iterations: 8	RMS: 0.1mm	RMS: 0.2mm	RMS: 0.2mm	RMS: 0.3mm
Subsample: 10% RMS: 1.5mm Iterations: 6	RMS: 0.1mm	RMS: 0.2mm	RMS: 0.2mm	RMS: 0.3mm
Subsample: 3% RMS: 1.5mm Iterations: 6	RMS: 0.1mm	RMS: 0.2mm	RMS: 0.1mm	RMS: 0.3mm

Table 2. Results for Tiles 9 and 10.
OP = oriented points, CP = corresponding points

HKTM → Res: 10mm **↓ Cyclone**	OP: 2000 CP: 55 RMS: 16.4mm Iterations: 4	OP: 800 CP: 24 RMS: 26.4mm Iterations: 2	OP: 600 CP: 15 RMS: 27.3mm Iterations: 3
Subsample: 90% RMS: 3.7mm Iterations: 38	RMS: 5.4mm	RMS: 1.9mm	RMS: 6.1mm
Subsample: 50% RMS: 3.7mm Iterations:17;	RMS: 5.5mm	RMS: 1.7mm	RMS: 6.1m
Subsample: 30% RMS: 5.0mm Iterations: 7	RMS: 5.7mm	RMS: 1.6mm	RMS: 6.3mm
Subsample: 10% RMS: 4.0mm Iterations:26	RMS: 5.8mm	RMS: 1.5mm	RMS: 6.2mm
Subsample: 3% RMS: 4.8mm Iterations: 6	RMS: 5.5mm	RMS: 1.8mm	RMS: 6.3mm

Table 3. Results for Tiles 6 and 7.

OP = oriented points, CP = corresponding points

HKTM → Res: 10mm **↓ Cyclone**	OP: 2000 CP: 21 RMS: 28.6mm Iterations: 6	OP: 800 CP: 22 RMS: 47.4mm Iterations: 6	OP: 600 CP: 15 RMS: 20.9mm Iterations: 7
Subsample: 90% RMS: 5.9mm Iterations: 16	RMS: 29.8mm	RMS: 35.5mm	RMS: 4.2mm
Subsample: 50% RMS: 6.6mm Iterations: 6	RMS: 29.8mm	RMS: 35.6mm	RMS: 4.5mm
Subsample: 30% RMS: 6.1mm Iterations: 10	RMS: 29.8mm	RMS: 35.6mm	RMS: 4.3mm
Subsample: 10% RMS: 6.3mm Iterations: 9	RMS: 29.9mm	RMS: 35.6mm	RMS: 4.6mm
Subsample: 3% RMS: 6.4mm Iteration: 55	RMS: 30.6mm	RMS: 36.5mm	RMS: 5.4mm

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. Before looking at the results is detail, it's worthwhile to note that for both Tiles data sets using 800 oriented points also appears to produce anomalous results. As the code for HKTM has been developed by various people over a period of time, finding if this is a "feature" of the program or just a coincidence is one that requires attention and will not be an easy task. The internal accuracy produced by HKTM for both data sets are similar at around 2 times the scan resolution, but both are significantly larger than the internal accuracy produced by Cyclone. This is 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.

Despite such poor internal results the external results for Tiles 9 and 10 and for using 600 oriented points for Tiles 6 and 7 are 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. Somewhat worrying are the 2,000 and 800 correspondence point orientations from Tiles 6 and 7. If the 800 correspondence point data set can be neglected for the above mentioned reasons, then external accuracy of the 200 correspondence point data set needs attention. What is comforting though is that there is no significant change in external accuracy as the Cyclone subsampling is reduced and the internal accuracy of Cyclone is very stable. This evidence all indicate that the use in HKTM of a more sophisticated registration algorithm such as ICP is worthwhile investigating.

7. 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. The selection of correspondence points requires the careful filtering of oriented points produced by the spin image process. After significant trouble in using the similarity measure of the original spin image matching process, a modification was made that recognises that an empty spin image cell is just as important in describing the shape of the surface around an oriented point as one that contains data. When tested with a data set (Bunny) used in the original spin image model and comparing the results with those produced by the Cyclone software it was found that the new methodology was sound. When testing with data more typical of what would be found in the slope monitoring world some questions as to the suitability of the registration algorithm used in HKTM were raised. Based on the findings of this research further development of HKTM will be on three fronts: the first is to use a more sophisticated registration algorithm such as ICP, the second is to investigate the existence of the 800 oriented point phenomenon and the third is to expand the capability of HKTM so that scans describing whole slopes, rather than just pairwise processing, can be undertaken.

9. Acknowledgments

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8. References

Besl, P.J. and McKay, N.D., 1992. A"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, Eric K. and Bruce King, 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.