AUTONOMOUS REGISTRATION OF LIDAR DATA TO SINGLE AERIAL IMAGE

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ABSTRACT

This paper proposes the use of phase correlation for the automatic registration of light detection and ranging (LiDAR) data and aerial imagery. First, buildings existent in the LiDAR data and aerial imagery are detected. Then the LiDAR data is interpolated to fixed point spacings, producing both a range image and a building binary mask. In the range image the pixel intensities correspond to the terrain's elevation and in the building mask the bright pixels correspond to buildings and dark pixels to everything else. A building binary mask is also produced from buildings detected in a corresponding aerial image. The Fourier transforms and the log polar Fourier transforms of both building binary masks are computed. Phase components are correlated and their peaks reveal the translation, rotation and scaling geometric transformation parameters. Results with real data are presented.

Index Terms— LiDAR, Registration, Building Detection, Pseudo Grid, Phase Correlation

1. INTRODUCTION

In order for a building detection and/or reconstruction algorithm to make use of features from multiple data sources, those sources must be registered (projected onto one another or describable by a single coordinate system). Because both LiDAR data and a single, overhead aerial image are either typically available or procurable for most desired terrains, these are the data sources considered. This paper proposes an automated procedure for registering LiDAR data to a single aerial image.

If both aerial image and LiDAR data exist for a given scene, then it behooves one to take advantage of the information existent in both sources of data for more accurate building detection and/or reconstruction. Several building detection/reconstruction approaches existent in the literature [4], [5], [10] treat the registration of the two data sources as a pre-processing technique and proceed to manually select corresponding control points in both sources and then perform the transformation projecting one image onto another. With the plethora of image registration methods published [11], several of which are automated, it is possible to instead automatically carry out this task.

The proposed registration scheme is implemented in the following steps: (1) detect buildings in LiDAR data; (2) interpolate LiDAR to fixed point spacings; (3) detect buildings in aerial imagery; (4) register detected buildings in LiDAR interpolated range image to aerial image. All of the above steps are illustrated in the block diagram representation in Figure 1:

![Figure 1 –Registration Algorithm Block Diagram](image)

2. PROPOSED INTERPOLATION METHOD

The phase correlation algorithm extracts the geometric transformation parameters from the Fourier transform space. Therefore, in order to use the algorithm, a two-dimensional Discrete Fourier transform of both the aerial image and the LiDAR data must be taken. The irregular LiDAR data must therefore be interpolated to fixed point spacing. There are several documented disadvantages to interpolating the data to fixed point spacing: interpolation errors; ambiguities introduced when multiple irregular points are reduced to a single, rasterized point which inaccurately attempts to describe both discrete ground and non-ground points [9]. Our intent is to use the registration algorithm to relate information extracted from the aerial image to the irregular LiDAR data to enhance an already existing building detection algorithm [8] and eventually help with building reconstruction.

Cho et. al. in [2] proposed a Pseudo Grid approach where a grid was overlaid on top of irregular LiDAR data. The points within a given grid space were interpolated and thus each grid made up a pixel in what became a range image. With this approach, the authors were able to keep track of the irregular points used for interpolation of a given rasterized point. Our proposed approach extends this concept to interpolation from a Triangulated Irregular Network (TIN). First, the irregular LiDAR data is triangulated using the modified Greedy Insertion
Triangulation algorithm described in [7]. Then, conceptually, a grid is overlaid on top of the triangulation, as shown in Figure 2.

Each raw point, bounded by a given grid cell, is stored in that cell’s data structure. Furthermore, the triangles whose vertices correspond to those raw points encompassed by the grid cell, are also stored in that cell’s data structure. The center of the square grid cell is also stored in that cell’s data structure. The elevation of that grid cell center is then calculated from the TIN (as it exists on one of the triangulated surfaces) and is also stored in the cell’s data structure. The triangle used to interpolate the grid cell’s elevation is also stored in that cell’s data structure. From this interpolation scheme, the irregular data is therefore closely tied to the interpolated data, as well as to the TIN, which will be related to the aerial imagery. The information extracted from the aerial imagery can therefore be applied to both the TIN and the irregular LiDAR.

In order to interpolate the grid cell center's elevation, its corresponding triangle, which encompasses the grid cell center, must first be found. This was done by implementing the following procedure. Suppose there are K total LiDAR points \( L(k) \) and P grid cell centers \( G(n,m) \) where P is equal to the product of the desired number of rows (M) and columns (N) in the interpolated range image:

\[
P = N \cdot M
\]  

(1)

The algorithm then proceeds to calculate the distance \( d(k) \) between all LiDAR points and the upper most left grid cell center:

\[
d(k) = \sqrt{[(L_x(k) - G_x(0,0))^2 + (L_y(k) - G_y(0,0))^2]}
\]  

(2)

Where \((L_x(k), L_y(k))\) are the longitude and latitude of the kth LiDAR point in the set of all LiDAR points. The point \((G_x(0,0), G_y(0,0))\) is the interpolated longitude and latitude coordinates (grid cell center) in the range image of the upper left most grid cell. The LiDAR point closest to that grid cell center is the vertex of one of the triangles which encompass that grid cell center. Therefore all of the triangles using that LiDAR point as a vertex are checked to see if they encompass the interpolated grid cell center. A triangle encompasses a grid cell center if the grid cell center point is bounded by the triangle's edges. Let's label the triangle encompassing grid cell center \( G(m,n) \) as the triangle \( T_{m,n} \).

The interpolated point's elevation is calculated using the planar equation which describes the encompassing triangle. After the first encompassing triangle \( T_{0,0} \) is found for the first grid cell center \( G(0,0) \), the search for the triangle \( T_{0,1} \) that encompasses the adjacent grid cell center \( G(0,1) \) begins. A region growing approach is implemented; the same triangle \( T_{0,0} \) which encompassed \( G(0,0) \) is checked to see if it also encompasses \( G(0,1) \). If the triangle \( T_{0,0} \), encompassing \( G(0,0) \), does not also encompass \( G(0,1) \), then all of \( T_{0,0} \)'s adjacent triangles are checked to see if they encompass \( G(0,1) \). If none of \( T_{0,0} \)'s immediately adjacent triangles encompass \( G(0,1) \), then all of the triangles adjacent to \( T_{0,0} \)'s adjacent triangles are checked to see if they encompass \( G(0,1) \), and so on and so forth. Once the triangle \( T_{0,1} \) (which may be equal to \( T_{0,0} \)) encompassing grid cell center \( G(0,1) \) is found, then the search starts for grid cell center \( G(0,2) \) where the region growing approach now starts with triangle \( T_{0,1} \).

### 3. PHASE CORRELATION REGISTRATION

It is impossible to develop a registration technique which will be optimal for all types of geometric transformations for all sources of images. Instead, the method must be optimized for the specific, required task. The two sources of data, an aerial image and LiDAR, are data captured from two different sensors. Furthermore, the overhead aerial image and LiDAR data are assumed to only differ via rotation, translation and scaling geometric transformations. By correlating the phases of the 2D Fourier transforms and phases of the log polar 2D Fourier transforms of the target and reference images, parameters for translation, rotation and scaling geometric transformations can be extracted [6].

The phase correlation method is an automatic, area based image registration algorithm; meaning that the algorithm operates on image intensity instead of control points or features such as corners, lines, etc. The aerial image intensity is obviously significantly different from the interpolated LiDAR range image intensity.

Because the two data are captured from two different sources, the technique cannot be applied without some preprocessing. We have chosen to use hierarchical, triangulated connected sets to detect buildings in irregular LiDAR data, as proposed by Shorter and Kasparis [8]. The connected set method identifies which triangles in a LiDAR
The phases of the LiDAR range image, applying approximate point density of 1 point per 1.3m. Fairfield, Australia. The procured LIDAR data has an square kilometers of both urban and residential scenery in the aerial imagery (producing a minimal scale change). The pixel resolution approximately equivalent to the resolution of point density by a factor of 9.66 resulting in an interpolated pixel spacing as the aerial imagery, thus resulting in a that the resultant range image has approximately the same density, then the interpolated LiDAR data is upsampled such apriori. By knowing both the pixel spacing and LiDAR point density can be calculated, if it is not also known apriori. The peak of the inverse of the phase correlation of the log polar Fourier transforms of the binary images reveals the scaling and rotation parameters while the phase correlation of the Fourier transform of the binary images reveals the translation parameters.

4. RESULTS

The Fairfield data set used for this research covers two square kilometers of both urban and residential scenery in Fairfield, Australia. The procured LiDAR data has an approximate point density of 1 point per 1.3m^2 and the aerial image, accompanying the LiDAR data captured, has 15 centimeter pixel resolution.

Phase correlation is limited for scaling translations from about 50% to 200% [1]. If the target and reference image (or in our case the range and aerial images) differ by scaling outside of the aforementioned range, then the phase correlation registration technique will fail. Pixel spacing in the aerial image are typically known apriori. The LiDAR point density can be calculated, if it is not also known apriori. By knowing both the pixel spacing and LiDAR point density, then the interpolated LiDAR data is upsampled such that the resultant range image has approximately the same pixel spacing as the aerial imagery, thus resulting in a minimal scale change between the two images. The range image was therefore upsampled from the LiDAR original point density by a factor of 9.66 resulting in an interpolated pixel resolution approximately equivalent to the resolution of the aerial imagery (producing a minimal scale change). The aerial image, shown in Figure 3, and LiDAR range image, shown in Figure 4, were of different image sizes and differ significantly in translation. The proposed algorithm, after extracting the geometric transformation parameters from the Fourier transforms of the binary images (Figure 5), applies those transformations to only the building areas in the range image thus registering those building areas on top of the aerial image with minimal error, as shown in Figure 6.

5. CONCLUSIONS AND FUTURE WORK

In this paper, we propose an interpolation method which extends Cho's pseudo grid approach by relating the interpolated grid cells not only to raw LiDAR points but to the triangles encompassing the grid cell centers as well. Furthermore, a region growing scheme for finding the triangles encompassing the grid cell center is also proposed. We also preprocess the range image and the LiDAR data, by creating binary building region masks, for the proposed use of phase correlation registration.

In the near future we plan to improve the building detection approach proposed in [8] by using this registration algorithm to enable us to draw upon corresponding features from both the LiDAR data and the registered aerial image to identify building regions. For now, the building regions are extracted manually from the aerial image. However, we are working on automatically detecting the buildings from aerial images to completely automate the entire process.

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7. REFERENCES
