ALGORITHM OF INTENSITY BASED REGISTRATION FOR TERRESTRIAL LASER SCANS

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ABSTRACT:

Laser scanning is a widely used survey technique which can be used for deformation analysis or 3D model creation. However, if scene is scanned from several points of view, the problem of point cloud correspondence arises. Registration of point clouds is an automatic procedure of data alignment, it finds matches between those parts of point clouds which are representations of the same objects. There are several known methods of registration such as ICP and 4PCS. Current article suggests a new one: an algorithm of registration based on radiometric features.

1. INTRODUCTION

Point cloud registration is the process to relate two point cloud sets that represent partially the same object from different points of view. This is done by finding transformation parameters so that the best match of the two point clouds can be achieved. Such algorithms as Iterative Closest Point (ICP) which was introduced by (Besl and McKay, 1992) and 4-Point Congruent Sets (4PCS) described by (Aiger et al., 2008) define a set of specific members which is called base for every point cloud. Then parameters of transformation between bases are calculated. Specific members of point clouds can be found based on uniform or random sampling as in ICP (Besl and McKay, 1992) or using coplanarity criterion as in 4PCS (Aiger et al., 2008). However ICP and 4PCS have several disadvantages: the first one requires initial registration, the second is based on finding sets of 4 coplanar members of point cloud presence of which is not guaranteed. That is why some new technique of registration can be useful. Basic idea of suggested method is generation of an image from every point cloud and calculation of specific members by keypoint detector.
Suggested algorithm does not require initial registration, but it uses image processing techniques which have some limitations and drawbacks. Advantages and disadvantages of the algorithm will be discussed further in this paper.
Algorithm was applied to the result of scanning of outside walls of Technical University Berlin (TUB) in order to illustrate generation of grayscale and colored images, histogram stretching and keypoint detection. After that it was applied to two point clouds which are results of scanning of the interior of TUB in order to detect keypoints and register point clouds between each other.

2. DESCRIPTION OF THE ALGORITHM OF REGISTRATION BASED ON RADIOMETRIC FEATURES

2.1 Image generation

Results of scanning can be transformed into an image because of the fact, that ptx-file contains values of intensity or RGB-components of points of object in a column-by-column manner. Numbers of columns and rows in the image are also provided in the ptx-file.

2.2 Histogram stretching

In order to improve the visual perception of the created image technique of contrast increase can be used. It emphasizes edges and contours, increases intensity differences between pixels. One of the contrast improvement methods is linear histogram stretching. This method finds minimum and maximum values of intensity on the image (I_{min} and I_{max}) and calculates new intensity I_{new} of every pixel based on its old value I_{old} by the following formula:

$$I_{new} = (I_{old} - I_{min}) * \frac{255}{I_{max} - I_{min}} \tag{1}$$

2.3 Keypoint detection

Detection of keypoints is done by Foerstner operator (Foerstner and Guelch, 1987). It uses the first partial derivatives of x and of y of the two-dimentional gaussian bell as a kernel for convolution to acquire gradients g_x and g_y of the image in x- and in y- direction. Based on these gradients the specific tensor for every pixel can be calculated using the following formula (Foerstner and Guelch, 1987):

$$T_{i,j} = \begin{bmatrix} \Sigma g_x^2 & \Sigma g_x g_y \\ \Sigma g_y g_x & \Sigma g_y^2 \end{bmatrix} \tag{2}$$

Tensor of the pixel characterises its neighborhood, shows if neighborhood contains homogeneous area, edge or interest point. All elements of the tensor close to 0 mean that strong gradients are absent in the neighborhood and the area is homogeneous . If one diagonal element has much bigger value than all the other elements of the tensor, there is a significant gradient either in x- or in y-direction, which means presense of an edge. If both diagonal elements are bigger than other elements, neighborhood has strong gradients both in x- and in y-direction which means that it contains a corner or a spot. The choise between these three cases is done by determination of weight w and isotropy q for each pixel. Weight defines significance of this pixel and its neigborhood as a point of interest (Foerstner and Guelch, 1987):

$$w = \frac{det(T)}{trace(T)} \tag{3}$$

Isotropy defines degree of similarity of gradient in pixel's neighborhood in different directions:

$$q = \frac{4 * det(T)}{(trace(T))^2} \tag{4}$$

Only pixels which have weight above threshold $w_{min} = c * w_{mean}$ and isotropy above threshold q_{min} are considered being interest points. Thresholds c and q_{min} are hyperparameters which define amount of detected keypoints: lower thresholds result in more points. Another hyperparameter is size of considered neighborhood which corresponds to estimated size of keypoints in pixels.

2.4 Keypoint matching and transformation calculation

Described algorithm of keypoint detection is applied for point clouds which are supposed to be registered. Current step looks for correspondences between keypoints detected from the image of source point cloud and image of target point cloud. It can be done by calculation of a descriptor which is a specific characteristic of each keypoint and calculation of similarities between diffirent descriptors. Algorithm of descriptor calculation is described in paper (Lowe, 2004), which describes the SIFT algorithm. This algorithm provides not only a point descriptor, but also a modern version of keypoint detector which has some similarities with the one presented in the current paper. SIFT detector also uses differences in intensity values in the pixel neighborhood as a measure of peculiarity of this pixel, but Foerstner detector uses first partial derivative of gaussian bell to describe this difference while SIFT uses difference-of-Gaussian function. Moreover, Foerstner detector deals only with 2 perpendicular directions of gradient (Luhmann et al., 2014) while SIFT uses gradient values to assign orientation and scale to each pixel and applies them later in order to provide invariance of descriptor to rotation and scaling. However SIFT detector shows rather slow performance and is not free software. That is why current article suggests an alternative to SIFT detector for the keypoint detection problem and usage of SIFT descriptor for the keypoint matching. Detailed information about SIFT descriptor can be found in the article (Lowe, 2004).

3. PRACTICAL IMPLEMENTATION OF THE ALGORITHM

3.1 Image generation

Grayscale and colored images generated from the point cloud acquired by scanning the exterior of TU is shown on Figure 1:

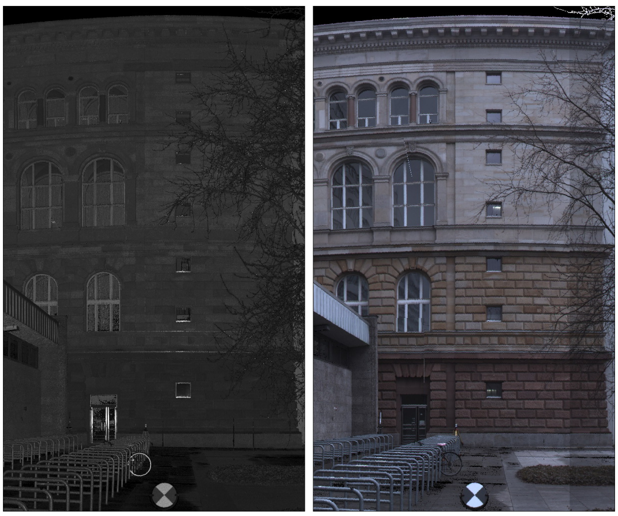

Figure 1. Left - Grayscale image of exterior walls; Right - Colored image of exterior walls

Although ptx-file provides intensity values with precision of 0.0001, image has only 256 possible values of intensity. Another possible intensity representation is (0; 65535), but in this paper the integer range (0; 255) is used. It means that intensities on the image are not so precise as in the point cloud representation, but this approach requires less computer memory for storage and processing. As it can be seen, the images are slightly distorted: eaves which in reality are straight lines are imaged as curves.

3.2 Histogram stretching

In order to assess contrast of the initial image the histogram is build and shown on the Figure 2:

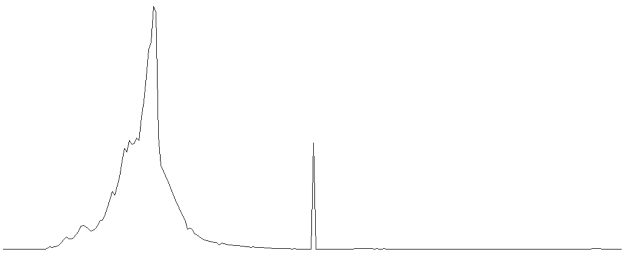

Figure 2. Histogram of original image shows number of pixels for grayvalues from 0 (leftside) to 255 (rightside)

The contrast is rather bad: several bright objects have very small sizes, the majority of pixels are dark, but black and near-black pixels are absent which means that contrast can be improved by engagement of these grayvalues. Minimum and maximum values of intensity are $I_{min} = 18$ and $I_{max} = 252$. It cannot be seen on the image of histogram of such a small size, but numerical representation of the histogram shows that the image contains several pixels in almost every bin of the right half of the histogram. Graphical representation of such bin is lower than one pixel, so these bins are not visible. The majority of pixels are darkgrey, but there is an unexpected narrow peak in the middle of histogram. Closer look at the data shows that many points have intensity equal to exactlly 0.5 and coordinates equal to 0.0. These points correspond to the objects with zero-reflectance, such as sky: laser impulse which is sent to the sky is not reflected at all, so coordinates and RGB-components of such points are equal to 0. Value of intensity for such points is defined by specific settings of hardware and software used for laser scanning. In order to make current algorithm invariant to such settings intensity of all pixels which have all 3 coordinates X, Y, Z equal to 0.0 is assigned to the same value of 0. The result of this operation is shown on Figure 3:

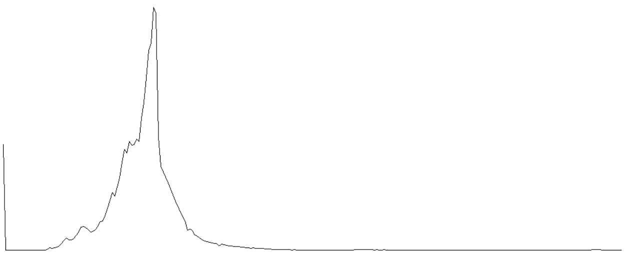

Figure 3. Histogram after assignment of intensity value 0

During histogram stretching all these pixels must be neglected. That is why pixels which have coordinates equal to 0.0 do not take part in calculation of minimal intensity value and are not influenced by histogram stretching, which is performed according to the formula (1) of current article and results shown on the Figure 4:

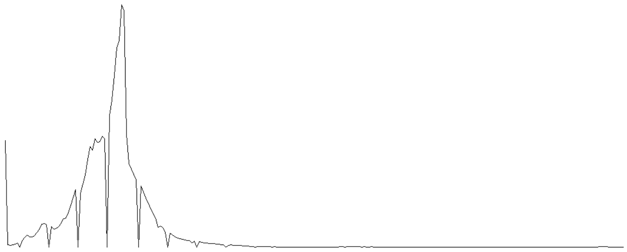

Figure 4. Histogram of grayscale image after stretching

This result illustrates the following disadvantage of linear stretching: if many values of intensity are presented in very small quantities (as it happens with all bright pixels of current image), output of stretching will be very similar to input. Although difference of intensities between rarely met pixels is not informative, they still belong to different bins of histogram and take part in calculation of minimum and maximum intensity of the image, which results in rather limited stretching.

3.3 Keypoint detection

Application of Foerstner operator to the image of exterior walls was performed using the following values of hyperparameters: size of kernel $k = 5$, coefficient c for weight threshold calculation equal to 1.5, isotropy threshold $q_{min} = 0.99$.

Result of the keypoint detection with these parameters is shown on Figure 5:

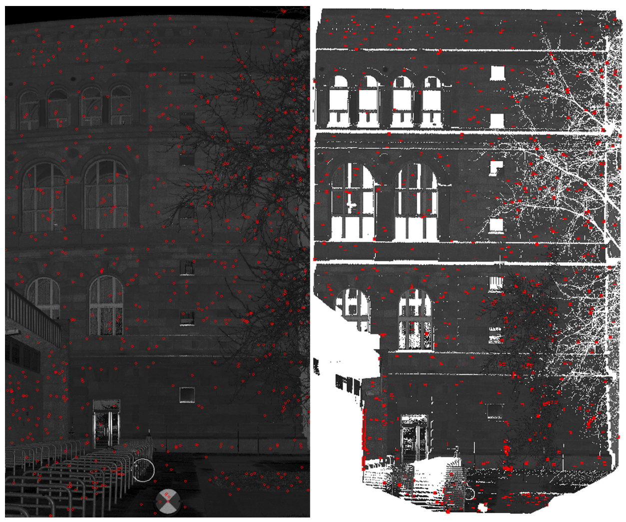

Figure 5. Left - Keypoints detected on the grayscale image; Right - Keypoints visualised together with point cloud

Since laser scanner uses spherical projection, the generated images are slightly distorted. Detection and matching of keypoints on distorted images can be not effective because of the fact, that distortion influences neighborhood of every pixel, neighborhood which is used to detect and match keypoints. One option of distortion influence reduction is usage of conic equal-area projections for the generated images, although resulting image will not be rectangular anymore. Another option is usage of projective geometry: calculation of matrices of internal and external orientation parameters and their application to the members of the point cloud in order to produce a non-distorted image by the following formula (Hartley and Zisserman, 2003):

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} \alpha_x & s & x_0 \\ 0 & \alpha_y & y_0 \\ 0 & 0 & 1 \end{bmatrix} * R * \begin{bmatrix} 1 & 0 & 0 & -X_C \\ 0 & 1 & 0 & -Y_C \\ 0 & 0 & 1 & -Z_C \end{bmatrix} * \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \quad (5)$$

, where x and y are calculated point coordinates on non-distorted image;
α_x and α_y - camera focal length in pixels in x- and y-directions, both taken equal to image size;
s - skew factor, taken as 0 for normal cameras;
x_0 and y_0 - pixel coordinate of principal point on the image, taken as half of the image size;
R - rotation matrix calculated from direction to point cloud centroid;
X_C, Y_C and Z_C - cartesian coordinates of the camera projection center, taken as (0,0,0);
X, Y and Z - cartesian point coordinates in the point cloud.

The results of such approach are shown on Figure 6:

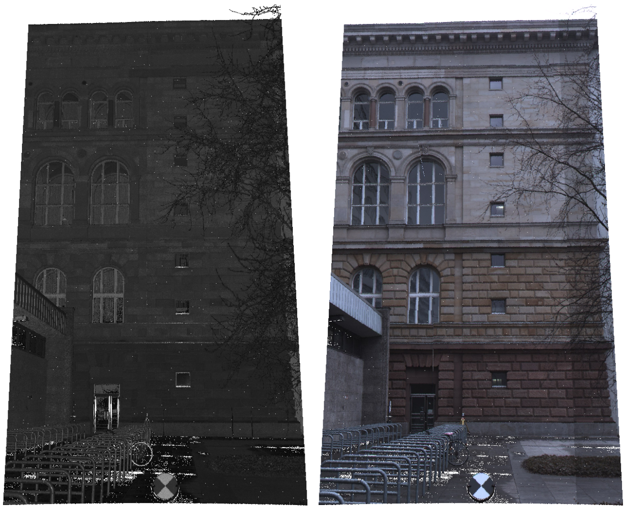

Figure 6. Left - Grayscale non-distorted image of exterior walls; Right - Colored non-distorted image of exterior walls

3.4 Keypoint matching and transformation calculation

Described algorithm of keypoint detection was applied to two point clouds which are results of scanning of interior of TUB. For this application values of hyperparameters were taken as following: isotropy threshold $q_{min} = 0.75$, size of kernel $k = 5$, coefficient $c = 1.5$. Figure 7 shows the generated images with four matched keypoint pairs, which are zoomed with colored rectangles in order to show their locations on the images. Matched keypoints are the following objects:
- corner of the PC monitor: in the purple rectangle;
- corner of the drawer: in the orange rectangle;
- corner of the desk: in the blue rectangle;
- upper right corner of the map on the wall: in the green rectangle.

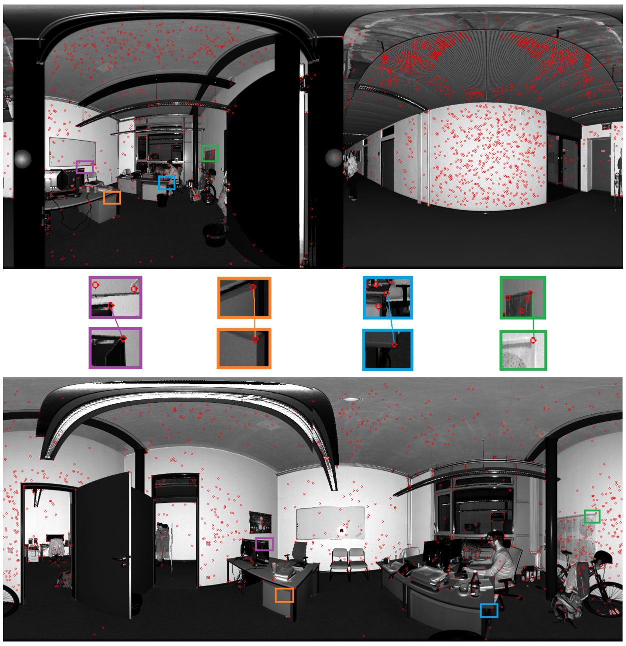

Figure 7. Upper - First image of interior with matched keypoints; Lower - Second image of interior with matched keypoints

These matched keypoints were used as input for the tool "Coordinate transformation calculation" in JAG3D software (www.javagraticule3d.sourceforge.net). This tool calculates the transformation matrix which is further used in cloud compare to register source and target point clouds. For the result of registration the calculation of cloud-to-cloud distance was done. Reference point cloud colored in grey and multicolored source point cloud are shown on the Figure 8:

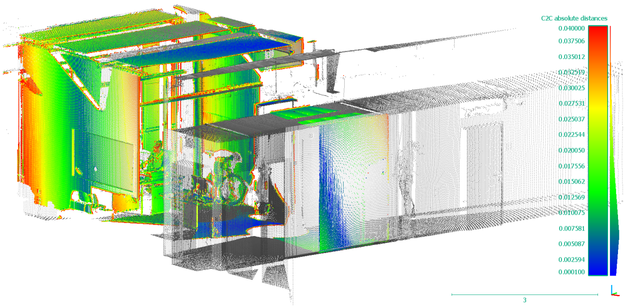

Figure 8. Greycolored reference point cloud and multicolored source point cloud still show significant differencies

The least distance between point clouds is found closer to the positions of scanners where the densities of both clouds are very high. Further from scanner distances tend to increase. Ceiling and floor are colored blue and green while walls show significant color gradient in 2 opposite horizontal direction which means that vertical registration is done good enough although angular horizontal registration is less accurate. In the left corner of the room differences between point clouds reach 40 mm (red colored points). That is why for fine registration ICP tool of CloudCompare can be used. Distances between point clouds after application of ICP are more satisfactory, they are shown on Figure 9 (here red color means 10mm difference):

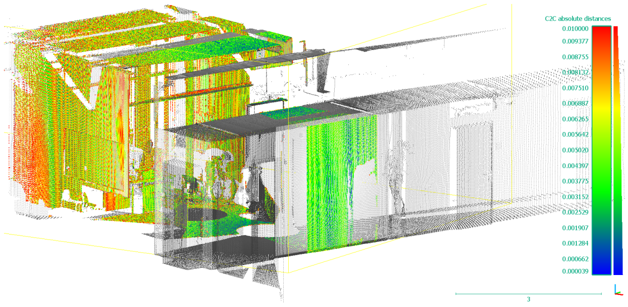

Figure 9. Registration of greycolored reference point cloud and multicolored source point cloud is improved by ICP

Now distances on the walls, ceilings and floor are much more uniform and are not bigger than 10 mm.

4. CONCLUSION

Suggested algorithm of registration based on radiometric features can be used as an independent point cloud alignment technique. It has some disadvantages such as non-invariance of applied Foerstner detector to rotation and scale or necessity to deal with image distortion and low contrast, but the suggested algorithm shows fast performance and does not need initial registration. Registration based on radiometric features can be used for initial registration itself. Its cooperation with ICP algorithm gives accurate results.

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