KEYPOINT DETECTION IN TERRESTRIAL LASER SCANS AS A PREREQUITE FOR INTENSITY BASED REGISTRATION AND TEXTURE MAPPING

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ABSTRACT:

One common basic approach to match in images is to detect suitable keypoints, which are spatial points that describe interesting and stand out information in the image. Many applications can benefit from keypoint detection in occurrence the keypoint detection in terrestrial laser scans for registration and texture mapping. Meanwhile, the challenge is to find accurate points that are invariant to any kind of distortions, less susceptible to noise and relevant for further image analysis tasks. Therefore, we need an approach to fulfil these requirements in order to get optimal interest points. A way to obtain the above distinctive points is to use keypoint detection algorithm such as Förstner operator, which consists to find the optimal points within the optimal window. We obtain successful results to the normal and tangent features while struggling with others.

1. INTRODUCTION

In the majority of fields of research, the accuracy of measurements is indispensable. In this work, we are interested in finding optimal interest points suitable for registering and mapping texture of terrestrial laser scans. The FÖRSTNER's operator was therefore preferred to the MORAVEC's operator due to its effectiveness in detecting and locating keypoint in image. The images in occurrence the coloured and greyscale were generated from intensity and radiometric point cloud information with slight distortion on them. In order to enhance contrast in image, histogram stretching as such a technique is analysed and discussed. Furthermore, a deep description of the Förstner algorithm, its parameters and its disadvantages is covered. Besides this, a theoretical comparison between the Förstner and the Scale Invariant Feature Transformation (SIFT) is done to evaluate the potentiality to use the second algorithm to clear bad points generated in the former algorithm while registering terrestrial laser scans and performing texture mapping operations. Finally, we visualize the detected keypoint with the original datasets as visual inspection tool to check the effectiveness of the Förstner algorithm.

2. RELATED WORK

There are many algorithms available for keypoint detection and localization in the scientific literature. The early 80s notably marked the genesis of such algorithms which were previously used in the field of stereo vision for image registration (Lucas and Kanade, 1981). Later on, the use of interest points or keypoint was initiated by (Moravec, 1981) and his work was improved by (Förstner and Gülch, 1987) and then (Harris and Stephens, 1988).

3. KEYPOINT DETECTION

3.1 Image generation

The current section describes the generation of both colour and greyscale images from terrestrial laser scans. The former image was defined based on the TU-Main-Building dataset, which gives point cloud with both intensity and RGB information. The second image was obtained by using only the intensity information from the Orangerie dataset, which is a smaller than the first dataset and contains similar information. The resulting images were adequate for further image processing steps such as keypoint detection without a major influence of noise and observed distortions.

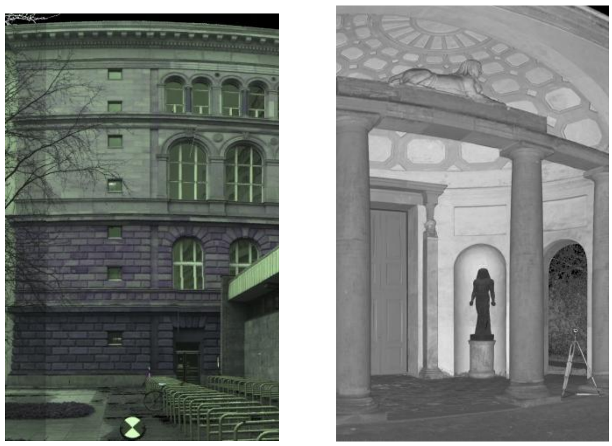

Figure 1. Generated colour and greyscale images

The developed software was able to handle complex steps such as the reading of pixel values and colour information from datasets and to generate colour and greyscale matrices. Then Open Computer Vision (OpenCV) functions were used to display and to save resulting images.

3.2 Histogram stretching

Histogram stretching technique is used to transform an input pixel to its enhanced output value. Stated otherwise, the contrast enhancement from the input pixel value to the output pixel value is based on a linear transformation. The parameters that rate the quality measures are the minimum and maximum greyscale values $g_{min}$and g_{max} of the image. By setting pixel values to $0\ (black)$, and its complementary range to $250\ (white)$ the range of pixel values does not map to a single greyscale value, thus causing the resulting image to appear less uniform. It is then suitable to set more than two parameters to specify the contrast stretch mapping in order to determine the position of the intermediate linear transformation and consequently to better enhance images.

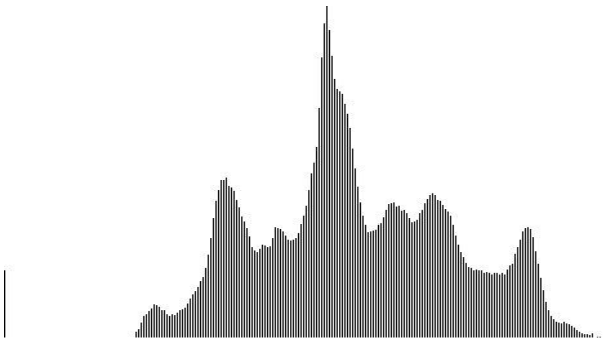

Figure 2. Histogram stretching Orangerie image

3.3 Description of the Förstner algorithm

The present section describes the Förstner algorithm which we use to detect keypoints. The ultimate goal is to detect the most distinctive, invariant, stable, and interpretable points in image. The Förstner operator is subdivided into two steps which are executed pixel wise, until the fulfilment of all above criteria to their highest degree. Initially, we need to search for optimal windows containing point likeness. Once this is done, we have to describe the point location by estimating the optimal point within the selected window (Förstner and Gülch, 1987).

3.4 Parameters of the Förstner algorithm

The implementation of the Förstner operator relies on the three metrics which are the structure tensor (A), the weight of the point likeness (w), and the roundness of the ellipse (q). In the former, we define the structure tensor (A) , which is an autocorrelation function (2x2 matrix) obtained by computing directional gradient in both x and y directions of each single pixel in image. Following the computation of its related Eigen values, one can differentiate homogenous area, edge and blob information within image. The second metric, the weight of point likeness (w) is calculated by dividing the determinant and the trace of the structure tensor. The last metric but not the least is the roundness of ellipse determined by dividing determinant of the structure tensor (A) by the square of its trace. In order to describe the location and the likelihood of a point to be an edge or to have a texture in a predominant direction, both the weight and roundness should simultaneously satisfy the below conditions: $w > w_{min} = (0.5, \ldots, 1.5). w_{mean}$ and $q > q_{min} = 0.5, \ldots, 0.75$ where q_{min} and w_{min} represent the minimum values of the roundness and weight of the optimal point within the optimal window (Luhmann, 2011, pp. 382). The Figure3 and Figure4 respectively illustrate the worst result and best results of the Förstner algorithm in our designed test image. We define acceptable weight and roundness values by randomly selecting and testing different values within the allowed range.

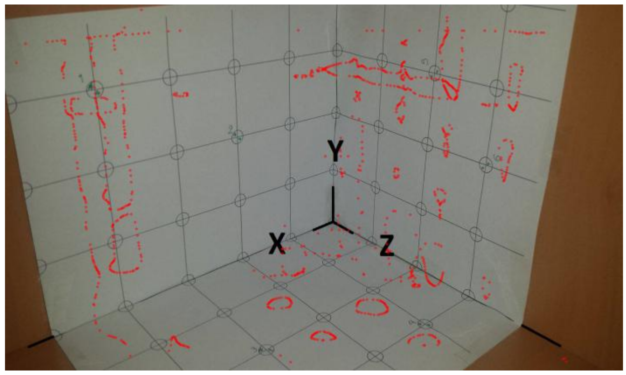

Figure 3. Worst tuneable Förstner parameters result on test image

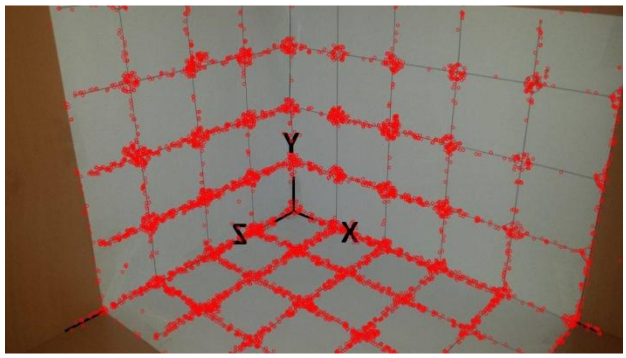

Figure 4. Best tuneable Förstner parameters result on test image

Therefore for the rest of our implementation, we assume that $\boldsymbol{q_{min} = 0.65}$ and $\boldsymbol{w_{min} = w_{mean}}$. These values have shown acceptable results.

3.5 Förstner and Moravec algorithm disadvantages

MORAVEC's operator performs a rather simple logic which just consists to only search for the optimal windows and to consider the centre of the defined windows as optimal point. The MORAVEC's operator results to the following weaknesses which are the lack of point distinctiveness and its incapacity to detect points on edges (Förstner and Gülch, 1987). In other hands, the FÖRSTNER's operator despite using a solid approach to determine the optimal point within the selected window fails to provide a good optimization of the point distribution. As a clue to this issue, the FÖRSTNER's operator should use adaptive threshold, which is a dynamic procedure to define threshold instead of setting a global threshold.

3.6 Förstner results on colour and greyscale images

The figure5 illustrates the results of keypoint extracted both in the colour and greyscale images. The difference is due to the contribution of each colour image channel by its noise level and gradient content. But essentially, the use of the FÖRSTNER's operator to colour image is quite similar to the process used in greyscale image.

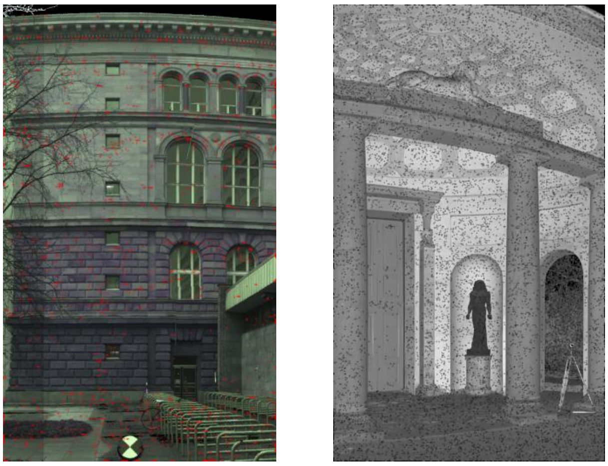

Figure 5. Keypoints on colour and greyscale images

3.7 Visualize of keypoint vs. original image

The visualization of both detected keypoint and the original Orangerie dataset illustrates a major presence of outliers that consequently do not allow the matching of the two datasets as shown in the figure6.

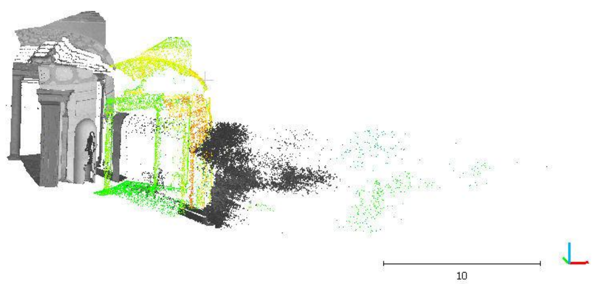

Figure 6. Visualization of keypoint and the Orangerie dataset

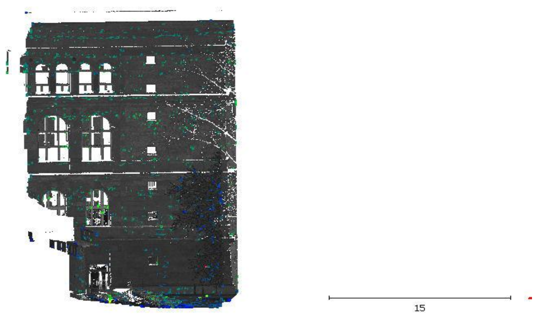

Figure 7. Visualization of keypoint and the TU Building dataset

The visualization of both detected keypoint and the original TU-main-building dataset illustrates absence of outliers and matching of the two datasets as shown in the figure7.

3.8 Compare the SIFT and Förstner algorithms

The scale invariant feature transform SIFT algorithm is well known for its robustness, image rotation, scaling, and translation. It is based on four major steps which are the construction of scale space image in order to find extrema based on the computation of difference-of-Gaussians. Finding and refining interest points using a second order Taylor expansion of the difference-of-Gaussians. Once the optimal position of keypoint estimated, histogram of the image gradients is used to calculate a descriptor in the region around keypoint. The above steps show that the complexity in estimating SIFT descriptor but also its robustness. In the other hands, the Förstner Interest Point Operator works in a two step procedure. In the first step, an optimal window is located. In the second step, optimal point is found. This approach is based on the computation of directional gradient in both x and y to compute normal and tangent features (Lowe, 2004).

4. CONCLUSION
5.

The article presented how windows and locations of optimal points in image were found (Förstner and Gülch, 1987). Meanwhile, the Förstner algorithm struggle to generate optimal points on our test image consisting on circle. This is due to the fact that obligue projection of a circle on a plane is an ellipse that has two focal points which may cause problems in deciding where a good centre should be located. Furthermore, we can explore how the polynomial affine transformation can be used to reduce distortion in terrestrial laser scans.

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