ON THE AUTOMATION OF THE REGISTRATION OF POINT CLOUDS USING THE METROPOLIS ALGORITHM

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ABSTRACT:

Surface measurement of complex geometric objects by means of optical measurement techniques, such as laser scanning or photogrammetry, requires multiple scans from various stations. The recorded data, e.g. distance images, photogrammetric images or point clouds, is given in independent coordinate systems. For further evaluation and a complete representation of the object, it is necessary to transform the surface describing point clouds into one common system. This step is denoted as registration, which exactly means the estimation of transformation parameters between the different coordinate systems. The main stages of the registration are the definition of the matching method, the execution and validation, and finally the calculation of the transformation parameters. In this paper a new operator is introduced which is capable of extracting features by consideration of point clouds as well as photogrammetric images. Features are first extracted in the images and then evaluated with the point clouds. Only features located in geometrically plane areas experience high probability of intervisibility from more than one view point. Based on this principle many investigations have been carried out to evaluate this operator. The quality and correctness of the selected correspondences guarantee the success of the automated registration. To match the candidates the stochastic optimization principle of Simulated Annealing (Metropolis Algorithm) is introduced. Finally, it is illustrated that the results of correspondence analysis confirm the theoretical investigations of the operator to registrate point clouds on a higher level of automation based on several data sets.

1. INTRODUCTION

The non-contact measuring technique of laser range sensors generates very efficiently three-dimensionally point clouds. For large and also complex objects, it is often required to acquire these point clouds from various stations. Thus, the point clouds existing in multiple coordinate systems have to be transformed into one common coordinate system.

Due to the desired high automation and the constraint of a non-contact measurement technique the registration should not be done by using synthetic markers. Hence an algorithm is necessary which can handle the point clouds of the scene directly.

The most well known algorithm for this registration part is the iterative closed point (ICP) algorithm introduced by Besl and Kay (1992). The closest points between the clouds are defined as corresponding candidates. That implies that the selected closest points depend on the approximate values of the rigid transformation of 6 parameters (3 translations, 3 rotations) between their local systems. These parameters are improved upon an iterative process.

To make the registration step more robust in terms of finding the global minimum, Gühring (2001) and Neugebauer (1997) proposed an extension of the ICP-algorithm. They found more reliable transformation parameters, by using additional information about the scanning device. Johnson and Kang (1997) also published a modified ICP-algorithm by using textured 3D-Data.

All the registration methods can be separated into the following stages that are listed below corresponding to Gühring (2002), Rusinkiewicz and Levoy, (2001):

a) Definition of the matching method
b) Execution and Validation
c) Calculation of the transformation parameters

The stages a) and b) are most relevant for the success of registration and are very important for the degree of automation of the full registration task. The last stage c) estimates the transformation parameters in a robust manner and is not considered in this paper.

Because of the importance of stages a) and b), they are formulated more robustly by using additional photogrammetric images. Beside the information of range and intensity images, photogrammetric images are available from a mounted camera on top of the scanning device (fig. 1). The system is calibrated and the exterior orientations of the RGB (red, green, blue) images are known in the scanners own coordinate system (SOCS).

Concerning the combination of the geometric and radiometric sensors, a new scanning technology is available for several years. With the availability of color coded point clouds (fig. 2) or textured objects, the generally higher resolution of the photogrammetric images offers new possibilities in the discrete processing stages. In the following chapter a new strategy is defined in detail, based on experience in digital image processing and geometric point cloud registration.

Figure 1: Combined sensor – laser scanner with mounted camera (RIEGL, 2004)

To evaluate the strategy, a data set containing the front of the main building of the University of Hannover, Germany is used. The data set is acquired with the Riegel LMS Z360 scanner and a mounted Nikon D100 with a 6 mega pixel image sensor. Several view points are available and due to known transformation parameters, it is also possible to control the registration step.

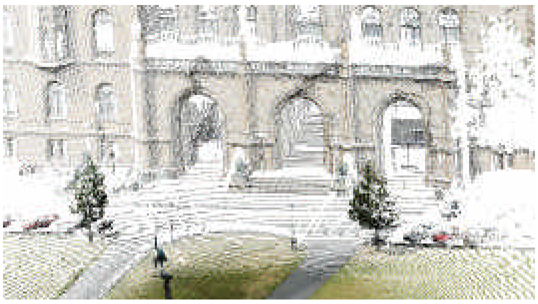


Figure 2: Color coded point cloud

2. DEFINITION OF THE MATCHING METHOD

The definition of corresponding candidates is also a question of the matching method. The task can be separated into low level and high level strategies. In the low level strategies the complete original data sets are used for registration. In this case, it is almost impossible to process the data it in an acceptable amount of time. In contrast to that, the high level strategies take much more effort in the preprocessing step to reduce redundant data and extract the most promising candidates.

In the following, a new operator is outlined in detail, which combines information from photogrammetric images and 3D point clouds for registration. It will be shown why the operator is image based, which role the point cloud plays and how wide baselines from different view points can be handled by the operator.

2.1 Image based point cloud operator (IBPCO)

The first issue is the necessity of invariant features in order to get the possibility to identify them from different view points. Much research has been carried out regarding that issue in the field of computer vision, (e.g. Van Gool et al., 2002, Polleyfeys et al., 2002, Lowe, 1999). More algorithms have been developed to extract features in the range images or point clouds (Lavallee and Szeliski, 1995).

Basically, all these algorithms try to extract distinct edges or corners in the data sets to identify them from different view points in a sophisticated manner. The major drawback of these algorithms is that the occlusion of some features - the corresponding candidates - causes these algorithms to fail. To be unable to assess the corresponding candidates before registration is unsatisfying for automation.

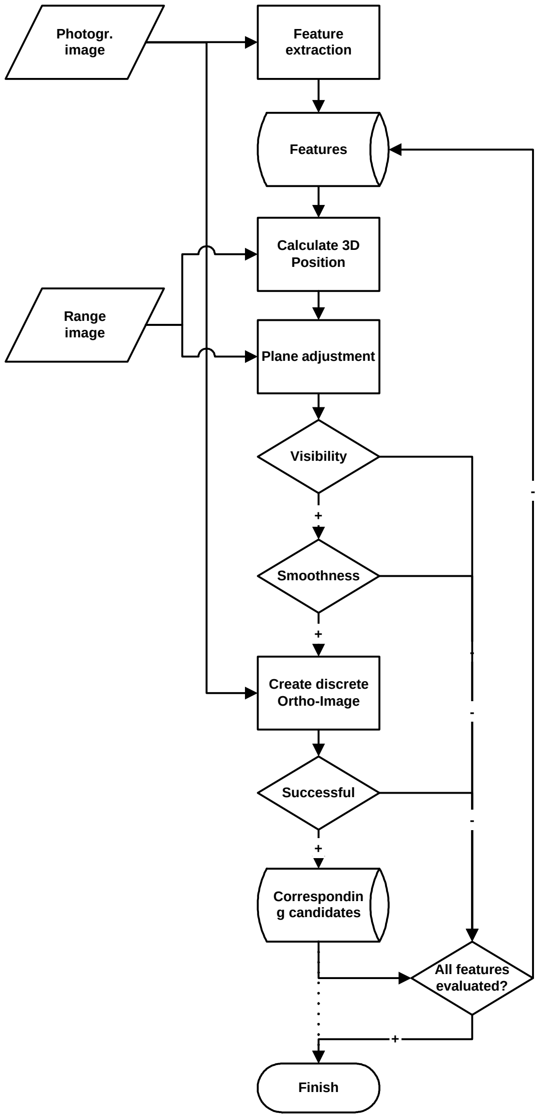


Figure 3: Image based search of corresponding candidates

The IBPCO is based on the fact, that high resolution images are available and oriented in SOCS and the assumption that some areas exist where sufficient texture for image matching is available. The goal is to identify reliably corresponding candidates by using the radiometric and geometric observations of the data set. The algorithm is based on the assumption that only features extracted in photogrammetric images and which are located in planar geometric areas could be suitable candidates (cf. fig. 3).

In the first step, distinct features have to be extracted with an appropriate operator for digital image processing. In this work the SUSAN (Smallest Univalue Segment Assimilating Nucleus) operator developed by Smith and Brady (1997) is used. In principle all pixels within a circular mask are compared with the nucleus. Therefore a threshold *t* has to be set according to the contrast and noise of the intensities to assign the pixels to the nucleus. The sum *n* of the comparison will be compared with a second threshold *g*. For a corner to be present, *n* have to be less than half of its maximum. Shortly, *g* predicates the geometric quality and *t* the density of the features.

Then the 3D position of the feature is interpolated from surrounding points (cf. fig. 4). For efficient processing the points are transformed into the image space of the camera under consideration of lens distortions of the used camera. As well as the position, an adjusted plane is estimated from these points.

The following inspection of visibility and smoothness is used to test the suitability of candidates (fig. 5). Depending on the set threshold for the max. viewing angle, the max. enabled baseline can be derived from. Features located in geometrically discontinuous areas can be separated due to points which differ from the estimated plane. These points can be detected with blunder detection in the plane adjustment or by calculating the curvature, the cosine angle between the normal vector and the difference vector of the interpolated 3D position of the SUSAN feature and the included points.

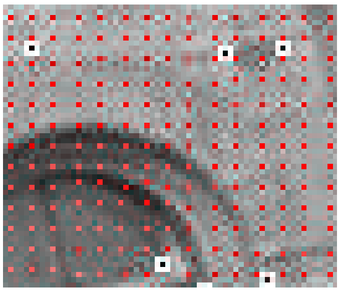


Figure 4: SUSAN features surrounded by 3D points. It shows some possible candidates with there surrounding points.

For the matching of the features which fulfill these conditions later on, a discrete orthoimage is calculated, consider the object space as is typically done in image matching, (e.g. Heipke, 1992). With this discrete image patch with an adequate size a reliable correspondence check is possible.

Therefore, firstly a grid is defined on the plane in object space, whereas the metric size of one facet is depending on the set image scale. Secondly, to fill the grid, each facet will be mapped into the considering image, then the grey values will be resampled bilinearly.

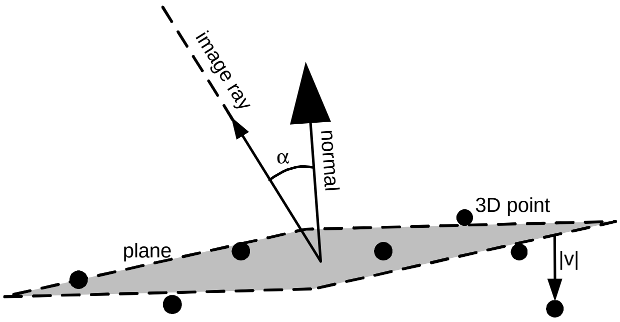


Figure 5: Visibility and Smoothness. The rulings of the geometric acceptance are defined on the one hand by the angle resulting from the scalar product between the normal and the image ray, and on the other hand by the max. absolute residual.

Here, also an inspection is necessary. Since the unavoidable comparability of the discrete orthoimages with candidates from different view points a fix image scale is set. The generation of the orthoimage can also fail if the SUSAN feature is located at the border of the image, meaning that not enough information is available to fill the grid.

However, until all features are evaluated the matching can be executed.

3. EXECUTION OF THE MATCHING METHOD

To match two sets of features from different view points, reliable criteria have to be defined to find the correspondences. Therefore a couple of possible criteria have been developed for this process based on the point clouds and the photogrammetric images.

3.1 Assessing criteria

Radiometric uniformity:

Is calculated with the cross correlation between the corresponding candidates. Due to the fact, that the patches have the same geometric resolution and the same orientation in object space, only the brightness have to consider what is regarded by the cross correlation. The resulting coefficient assesses the uniformity.

$$r_{fg} = \frac{s_{fg}}{s_f \cdot s_g} \tag{1}$$

Intensity:

The scanning device supplies the intensity for observed 3D points, with which the active signal is reflected on the surface of the object.

$$E_{INT} = Abs(C_I - P_I) \tag{2}$$

Neighborhood:

The assessment of the neighborhood is only possible in a final post process. It can be done directly in three-dimensional object space or more efficiently in image space. Due to the rectified zaxis (perpendicularity) during the whole data acquisition from the different view points of the scene, the ascending order of the corresponding candidates in the different evaluated feature lists is identical, which will be described more detailed in section 4.

$$E_{TOP} = f(P_{Neighbor}, C_{Neighbor}) \quad (3)$$

3.2 The matching strategy

Due to the fact that the amount of accepted features can be controlled by the rigidity of particular thresholds, a simple strategy for the matching is to assess all possibilities of combinations. This is only possible if criteria can be used whose influence is restricted to the individual point.

For combinatorial criteria optimization methods, e.g. graph cuts (Huber et al. 2001) or Simulated Annealing (Weisensee and Wendt, 2003, Luck et al., 2000) have to be used. To avoid optimization methods Chen et al. (1999) used a modified RANSAC (Random sample consensus) method. They randomly select the minimum size of sets to estimate the transformation parameters and assess the solution. They stop their algorithm, when the consensus is found.

In the following the metropolis algorithm is briefly introduced, to give an idea about the principle (cf. Press et al. 1992).

3.2.1 Simulated Annealing – the Metropolis Algorithm

The term annealing originates from the controlled heating and cooling of material, e.g. metal. In case of liquefied metal a slow cooling leads to a regular structure having a low energy level while a fast cooling leads to irregular structure at a high energy level. In a controlled operation of heating and cooling the energy of the material rises temporarily but in total it can be reduced to a global minimum. Thus, the metal is tempered. The transfer of this principle to a procedure for the allocation of corresponding candidates leads to an algorithm as shown in fig. 6.

The solution for the unknown corresponding candidates is initialized by random numbers. Depending on the energy of the initial solution a starting value for the equivalent of the temperature T_0 is determined. The relation given in equation (4) has been derived in (Weisensee, 1992) to assure that a new correspondence will be accepted by the algorithm at temperature T_0 according to equation (5) with a probability of approximately 0.5 even if the energy of the system increases.

$$T_0 > \Delta E * 1.4 \quad (4)$$

Starting from this temperature the system is cooled down after it has reached the equilibrium, i.e. when the energy of the system does not decrease any more or if a specified number of iterations have been processed. Until equilibrium is achieved, new corresponding candidates are randomly allocated. They give rise to a change of energy ΔE compared with the previous solution. A new solution is accepted always if the energy decreases. Otherwise, it is accepted with a probability

$$W(\Delta E_{(X)}) = e^{\left(\frac{-\Delta E_{(X)}}{k * T_i}\right)}$$

with $T_i > 0$, k = Boltzmann constant (5)

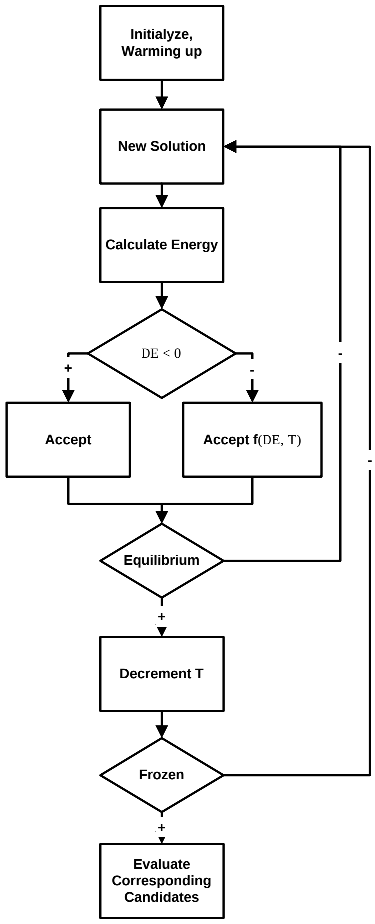


Figure 6: Principle of the metropolis algorithm

depending on the change in energy ΔE and the current temperature T_i of the system. The temperature is reduced by a constant factor q_C which leads to a geometric series of numbers

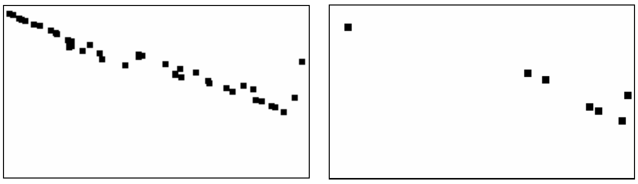
$$T_{i+1} = T_i \cdot q_C \quad \text{with} \quad q_C > 0. \quad (6)$$

This scheme is repeated until the system is frozen.

4. VALIDATION OF THE MATCHING METHOD

Here, the processing of the data set is described. First the features will be extracted with the IBPC operator. For the corner extraction with SUSAN a radiometric threshold of t=20 grey values and g = 50% of the area of the circular mask is used. For the geometric acceptance a viewing angle of max. 60° is allowed and a max. point residual of 300 mm to the adjusted plane. The discrete 31 x 31 pixels orthoimage is calculated with a resolution of 30 mm per pixel in object space. The amount of SUSAN features per photogrammetric image is reduced from approximately 10 000 to approximately 500 features.

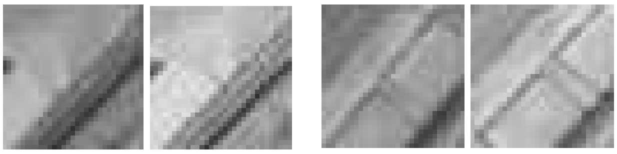
For the validation all possible combinations of candidates are calculated. Only the combinations with a non-ambiguous correlation coefficient in relation to the other solutions are accepted. Here, the threshold is set that the largest correlation coefficient is 10% larger than the second largest. This gives reason for the rejection of a lot of IBPCO features in areas of low or repeatedly texture (fig.9).



a) True correspondences b) Accepted correspondences

Figure 7: A selection of the corresponding features

In fig. 7 a) a selection of the true correspondence matrix is visualized which is calculated from the known transformation parameters between the point sets. The mentioned neighborhood of the features is evident within the cluster in the matrix. Obviously, in the upper left and lower right part no correspondences exist, because the used cloud patches do not cover the same scene completely. Fig 7 b) shows the result of the accepted correspondences. They are located in a preferred area where the viewing angle is almost collinear to the normal of the discrete object.



a) True correspondence b) False accepted correspondence

Figure 8: Discrete orthoimages of true and false corresponding candidates

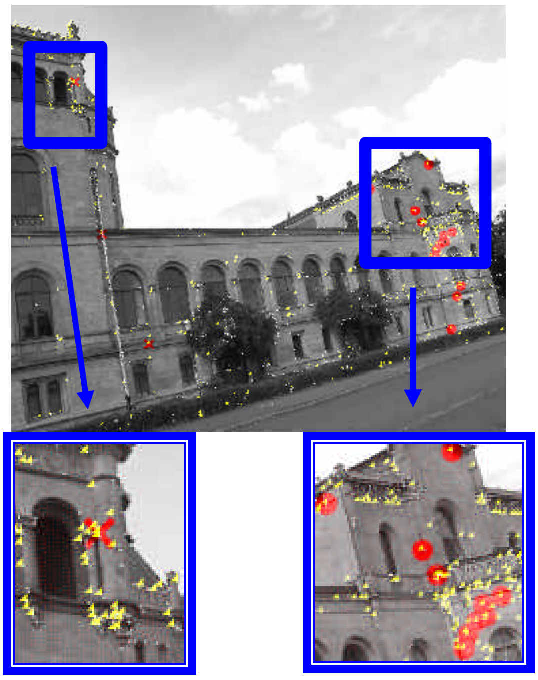


Figure 9: Distribution of matched correspondences

However, more than 80% of the accepted 16 correspondences conform to the true candidates. In fig. 8 an example for a true and a false accepted correspondence is provided. Because of the repeated texture, the candidates can not be clearly distinguished. In contrary, larger grids of the discrete orthoimages would reduce this problem. Fig. 9 visualizes the distribution of the accepted correspondences. The correspondences are highlighted with a red circle. Further all extracted features of the IBPCO process in the used scene are highlighted with yellow triangles. The falsely accepted correspondences are highlighted with a red cross.

It has been illustrated, that possible corresponding candidates (yellow triangles) are located in the whole scene. At the same time only some regions show sufficient texture patterns for successful cross correlation. In addition to the possible enlargement of the discrete orthoimages, further attributes are needed to differentiate the candidates. For demonstration, in fig. 10 the resulting value of the SUSAN operator is used to refine the matching strategy. The figure shows the candidates of the highest similarity. The goal is to find the adequate weights between all included criteria. Further investigations have to be made for such weighting strategy.

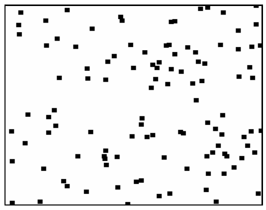


Figure 10: Corresponding features matched with the resulting SUSAN value

5. CONCLUSIONS

In this research the strength of the combination of laser range devices and photogrammetric images is shown for registration purposes. An operator for feature extraction is developed based on experience in digital image processing and point cloud registration. The concept is introduced and validated with a selection of the clouds of two view points. The results of the accepted correspondences are analyzed. False correspondences occur in cases of ambiguous texture. It is explained how to reduce such cases by using larger grids for the cross correlation.

For the last stage, the calculation of transformation parameters from the accepted correspondences a robust method is needed. Therefore RANSAC (random sample consensus) published by Fishler and Bolles (1981) is a good strategy to detect the blunders. Thus, a success of 80% of true candidates is enough for a reliable registration. More important is the distribution of the candidates, which should be supervised by the neighborhood or topology of the candidates.

Further investigations will be necessary to analyze the presented operator in more detail. Especially the thresholds according to the locally geometric situation should be controlled automatically in an intelligent way. Also different investigations will be made to judge the texture of the discrete orthoimage, e.g. with the Haralick parameters, (cf. Luhmann, 2000), that have to implemented in the IBPCO.

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