REGISTRATION TOGETHER AND TO DSM OF SEVERAL 3D POINT CLOUDS ISSUED FROM A MOBILE MAPPING SYSTEM

Taha Ridene and François Goulette
Mines ParisTech, CAOR- Centre de Robotique, Mathématiques et Systemes,
60 Bd Saint Michel 75272 Paris Cedex 06, France
Tel: 01 40 51 93 27 (92 35) - Fax: 01 43 26 10 51
taha.ridene@mines-paristech.fr, francois.goulette@mines-paristech.fr

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ABSTRACT:
The development of 3D mapping databases is a matter of increasing interest. Databases have recently been developed at different scales (national, European, international) and to meet different needs. Such development has been made possible by the implementation of efficient 3D mapping technologies. 3D mapping strategies are based on multi-sensor data fusion usually performed after a preprocessing step that includes registration and filtering. In this paper, we present our work on registration methods applied to resolve problems on 3D urban environment representations issued from a Mobile Mapping System.

1 INTRODUCTION

The development of 3D mapping databases is a matter of increasing interest. Databases have recently been developed at different scales (national, European, international) and to meet different needs. Different methods have been used to develop such Databases. The expansion of this development has been made possible by the implementation of efficient 3D mapping technologies and rapid progress in various fields such as remote sensing, image processing and sensor technologies (camera, laser, GPS, INS, etc.). A variety of efficient Mobile Mapping Systems (MMS) have been produced to create 3D models of cities. MMS are special vehicles which integrate two kinds of sensors: “positioning sensors” (GPS, INS, Compass, etc.) and “sensors of perception” (camera, Laser, radar, etc.). Acquisition with MMS can be carried out using two methods: “driving” and “Stop and go”. After the acquisition data step, we processed the resulting data sets using algorithms of multi-sensor data fusion to obtain 3D representations. To do that so (acquisition, processing) specific software such as RT-Maps (Nashashibi et al., 2000) was used, which generates a timestamped data bases. Most land MMS use “direct geo-referencing,” a category which can be divided into two sub classes in linked with 3D perception sensors: (1) Laser-based (Goulette et al., 2006, Zhao and Shibasaki, 2003); (2) photogrammetry-based (Bentrah et al., 2004, Pollefeys et al., 2008). However, there are also MMS using “indirect geo-referencing” (Früh and Zakhor, 2004). The results produced by MMS depend on the sensors used. A comparative study between MMS can be found in (Ellum and El-Sheimy, 2002, Schwarz and El-Sheimy, 2004).

1.1 Context

Under the project we aim to generating realistic and geo-referenced 3D maps of urban areas around Paris. We use mainly our Mobile Mapping System (MMS) Lara3D (Goulette et al., 2006) presented in Figure 1. In the present work we made acquisitions using Lara3D in the 5th district of Paris, around the Town Hall. These acquisitions were with the “driving method” and planned by road sections. In fact, in a dynamic urban environment with obstacles (cars, streetlights, etc.), it is impossible to treat all sections of the area at once. A series of acquisitions must thus be made. The resulting of multitude of separate acquisitions generates incoherence in the producing data (i.e Figure 2) due to the problems that may affect sensors (GPS multi path error, GPS masking, INS drift, etc.). Despite the geo-referencing we observe offsets and deformations between the datasets. To obtain a correct model at the end of processing, we have to apply registration of the data sets before using the fusion step and to make a correct registration, we need 3D reference data. We have two possibilities: (1) register overlapped road sections by pairs. (2) carry out registration by using external 3D representations as references; In our case we used a Digital Surface Model (DSM) (i.e Figure 3). In fact, data of the DSM is the most extensive for this area and provides the best geo-referencing in absolute terms. This combination between DSM and MMS point clouds is useful for the final model. The main contribution of the fusion between these two 3D representations lies in the fact that they complement each other (for example : roof information that is not accessible by Lara3D acquisitions can be recovered from aerial data (DSM), so the ground track of the buildings hidden by the edges of roofs in a DSM will be accessible by the Lara3D data set).
Figure 2: Superposition of all road sections produced by Lara3D around the Pantheon (each road section with a specific color). Three different view angles were presented. We observe problems of coherence between road sections. This is due to the localization problem of MMS in the urban environment: GPS multi path error, GPS masking, INS drift.

1.2 Contributions

The main contributions of this paper can be stated as follows. First, we present a variant of rigid registration based on ICP with preprocessing. This variant is adapted to our heterogeneous datasets and uses two different adjustment techniques suitable to the cases studied. Second, a classification of cases of registration related to the kind of overlap which makes it possible to improve the performance of the algorithm and to set the input variables. Third, the proposed registration variant is applied to two datasets that have a different amounts of geometric features along with different resolutions and levels of precision captured using two different techniques (Mobile laser scanner and DSM).

This paper is organized as follows. In section 2 we present a state of the art of rigid registration and our implementation is described. In section 3 the experimentation relating to identified scenarios and results are shown. We then present our conclusions and perspectives for future works.

2 REGISTRATION

2.1 State of the art

Rigid registration consists in estimating a rigid transformation between two data sets which provide a representation in the same referential. To register three-dimensional representations, the most widely-used approach is the Iterative Closest Point (ICP) introduced by (Besl and McKay, 1992, Chen and Medioni, 1992, Zhang, 1994). In the ICP algorithm described in (Besl and McKay, 1992), two main steps are provided. (1) Generation of a set of matching pairs: each point in one point cloud is matched with the closest point in the other point cloud to form correspondence pairs. (2) Estimation of rigid transformation; use a point-to-point error metric, is used the sum of the squared distances between points in each correspondence pair is minimized by rigidly transforming one of the point clouds. These two steps are iterated until stabilization (the error becomes smaller than a threshold or it stops changing).

It has been demonstrated that the ICP converges to a local minimum, but this convergence is determined by the initialization at the beginning of processing. In the case of urban 3D representations, if all treated data sets are geo-referenced in the same referential, this referencing will be considered as initialization of the ICP.

Different variants of ICP were proposed in previous works related to rigid registration used in different fields of application (computer vision, photogrammetry, artificial intelligence, etc.). Comparative studies of ICP variants were provided in (Rusinkiewicz and Levoy, 2001, Gruen and Akca, 2005, Akca, 2007). However, there is no guarantee that registration of two 3D point clouds using the ICP will be successful. Registration can fail due to several causes. (1) If the overlap between the two 3D point clouds is small and not determinist. (2) If data input measurement errors are too big. (3) When there is insufficient geometric constraint on the 3D transformation between the two 3D point clouds (for example, when a plane is being registered to a second plane).

2.2 Proposed registration method

Preprocessing operators were applied to input data sets: (1) 2D Morphological filtering was performed on the DSM to reduce noise, an Alternate Sequential Leveling (Soille, 2003). (2) Sub sampling was performed on Lara3D point clouds to reduce search space and to focus the registration on the area of interest. To determinate points of interest we use all points resulting from a preprocessing step as in (Besl and McKay, 1992).
We find the homogeneous coordinate transformation matrix $T = [R|t]$ which has six free motion parameters (3 angles and 3 translation components) that minimizes a registration error $\epsilon$ between two point clouds using the linear equation 2. (Horn et al., 1988) method is used to minimize and to determine $T$.

$$\epsilon = \frac{1}{N} \sum_{i=1}^{N} || P_{i} - (RP_{i} + t) ||^2$$ (2)

We use point-to-surface distance (Chen and Medioni, 1992) (i.e Figure 4.b) for registration between Lara3D point clouds. In fact, the quality of data shows a regular density in 3D dimension and this kind of adjustment can be used. Still, for Lara3D/DSM registration we use point-to-point distance (i.e Figure 4.a). In fact the DSM geometry is a 2.5D and we have irregularity in the Z dimension on 3D representation. It is thus not possible to use the previous adjustment technique.

We have established an approach of rigid Registration ICP using a dynamic threshold as in (Masuda and Yokoya, 1994; Fitzgibbon, 2003) with duplicate pairs of correspondence removed as in (Almhdie et al., 2007).

Initialization was provided on the dynamic Threshold according to equation 3.

$$Th_{D_{y}} = \kappa \cdot \arg \max \{ Res(P1); Res(P2) \}$$ (3)

The large amount of processed data (6 million points in our case) results in a huge computation time, which can have a limiting impact in practical cases. To accelerate our implantation we optimized the search process of nearest neighbors by using a K-D Tree according to (Mount and Sunil, 2006).

The computational complexity has been reduced from $O(n_{b1} \cdot n_{b2})$ to $O(n_{b1} \cdot \log(n_{b2}))$ with $(n_{b1}$ and $n_{b2}$ representing the number of points in point clouds inputs.

2.3 Scenarios of registration

Our aim was to register Lara3D point clouds which have coherence problems. We performed the registration in two steps. Firstly, we did a rigid registration between 3D point clouds issued from MMS using the transformation matrix $T1$ provided by two sections each time. We then did the registration for the final result with DSM using the transformation matrix $T2$. Equation 4 shows the steps of registration in terms of transformations used, which $P_{result}$ and $P_{init}$ refer to respectively as the result point cloud after registration and the initial point cloud before registration.

We planned two scenarios of registration:

- Registration between Lara3D datasets : we classified it that on three groups according to the kind of overlap (extremity, intersection and partial part). Figure 5 shows all cases of the registration in this scenario.
- Registration of the Lara3D data set on DSM : for each registered case of the previous scenario, a reference road section was selected and we performed registration on the corresponding area on the DSM. The $T2$ transformation result was then applied for the second road section for each case.

$$P_{result} = (T1 \circ T2)P_{init}$$ (4)

3 RESULTS AND DISCUSSION

We apply registration with an adaptive threshold on 3D datasets of outdoor urban representation. In our processing we distinguish two steps (i.e Figure 5). (1) Registration by pairs between Lara3D point clouds: the set of registration includes four cases corresponding to different forms of overlap. The case of $P5$-$P2$ with intersection was not treated due to problems in $P5$ point cloud quality. (2) Registration for the reference road section of each registered pair in the previous step with the corresponding area on the DSM: the set of registration includes 2 cases. We evaluated our results in a comparative study in terms of convergence speed, complexity and average registration error. Initial values for variables needed for the processing are presented in Table 1. Table 2 shows the computing time for each treated case of registration. Testing of the algorithm was performed on a PC Intel(R) Xeon (R) CPU 5130 @ 2.00GHz with 2Go of RAM.

3.1 Registration between MMS point clouds

For each road section produced by Lara3D it was necessary to carry out registration to correct the geo-referencing. Five cases...
Table 1: Initialization of values for different variables for ICP.

<table>
<thead>
<tr>
<th>Variable</th>
<th>$\Delta \text{error}_{\text{min}}$</th>
<th>$\kappa$</th>
<th>$K_{\text{max}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lara3D/DSM</td>
<td>30 cm</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>Overlap on extremity</td>
<td>15 cm</td>
<td>30</td>
<td>100</td>
</tr>
<tr>
<td>Partial overlap</td>
<td>15 cm</td>
<td>20</td>
<td>100</td>
</tr>
</tbody>
</table>

Three different initializations were performed according the treated use case.

of registration were treated according to the kind of overlap (i.e Figure 5).

Figure 6 shows an example of registration when we have an overlap on the extremity: the case of Soufflot Street between P1 and P2. The geo-referencing problems are visible, and the road sections are not consistent. After registration we obtained coherence between P1 and P2. Figure 8 displays the algorithm behavior with point-to-point (P-to-P) adjustment and point-to-surface (P-to-S) adjustment. P-to-S adjustment produces a little better result compared to P-to-P in terms of convergence. In fact in P-to-S the result was established on average error 0.13m after 25 iterations compared to 0.15m for P-to-P.

Figure 7 gives an example of registration when we have a partial overlap: case of Soufflot Street between P3 and P4. The geo-referencing problems are visible, and the road sections are not consistent. After registration we obtained coherence between P3 and P4. Figure 9 displays the algorithm behavior with P-to-P adjustment and P-to-S adjustment. P-to-S adjustment produces a better and more accurate results than P-to-P in terms of convergence. In fact, in P-to-S the convergence was obtained on average error 0.14m after 37 iterations compared to 0.32 after 35 iterations in P-to-P when convergence was not obtained.

We note that the adjustment methods do not influence the results of registration in the case of overlap on the extremity, unlike the case of partial recovery in which the P-to-S method produces a better and more accurate result than the P-to-P method.

3.2 Registration between MMS point clouds and DSM

For each registered pair in the previous step we chose a reference road section and then registered it with the corresponding area in the DSM. Two cases of registration were treated: P2-DSM and P6-DSM. Figure 10 shows an example of registration on Soufflot Street P2. We did a filtering on the DSM to reduce noise. We used an initial transformation $T_{\text{init}}$ to help the algorithm to converge. The result was correct, and thanks to the initialization the result was established on average error 0.32m after 31 iterations. Figure 11 displays the algorithm behavior with and without initialization.
4 CONCLUSIONS AND FUTURE WORK

In this paper, we have proposed an alternative solution for MMS problems, when the direct geo-referencing fails. It is based on rigid registration applied between only two point clouds at the same time. The registration is decisive in resolving problems which appear when we perform MMS acquisitions in an urban environment. We performed the registration in two steps for 2 scenarios. Firstly, we did a registration between pairs of MMS road sections. Secondly, we perform a registration for reference road sections of each pair registered in the previous step, with DSM external 3D representation reference. In our application we treated very large data sets of points (6 million points). To accelerate the processing time we use K-D Tree. Hence, we obtained acceleration by a factor of 32. A quantitative study based on evaluation of convergence was run to improve the quality of results.

Qualitative registration evaluation is useful as it renders comparison between registered trajectories and reference PPK-GPS paths possible.

In the case of accumulation of errors in data issued from positioning sensors (GPS,INS), 3D point clouds resulting from MMS acquisition will be affected by local geometric deformations. In such cases, rigid registration fails and cannot give a good result. In such situations, we have to use a non rigid registration method to correct topologies of input datasets during the registration process. Figure 12 shows an example of registration which needs a non rigid registration.

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REFERENCES


