SIMULTANEOUS CO-REGISTRATION AND GEOREFERENCING OF MULTIPLE POINTCLOUDS

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ABSTRACT: A method for the simultaneous co-registration and georeferencing of multiple 3D pointclouds and associated intensity information is proposed. It is a generalization of the 3D surface matching problem. The simultaneous co-registration provides for a strict solution to the problem, as opposed to sequential pairwise registration. The problem is formulated as the Least Squares matching of overlapping 3D surfaces. The parameters of 3D transformations of multiple surfaces are simultaneously estimated, using the Generalized Gauss-Markoff model, minimizing the sum of squares of the Euclidean distances among the surfaces. This method can be applied to data sets generated from aerial as well as terrestrial laser scanning or other pointcloud generating methods.

1. INTRODUCTION

Terrestrial laser scanning companies (e.g. Z+F, Leica, Riegl) commonly use special kind of targets for the registration of point clouds. However such a strategy has several deficiencies with respect to fieldwork time, personnel, equipment costs, and accuracy. In a recent study, Sternberg et al. (2004) reported that registration and geodetic measurement parts comprise 10-20% of the whole project time. In another study a collapsed 1000-car parking garage was documented in order to assess the damage and structural soundness of the structure. The scanning took 3 days, while the conventional survey of the control points required 2 days (Greaves, 2005). In a recent project conducted by our group at Pinchango Alto (Peru) two persons set the targets to the field and measured with Real-Time Kinematic GPS in 1½ days.

Not only fieldwork time but also accuracy is another important concern. The target-based registration methods cannot exploit the full accuracy potential of the data. The geodetic measurement naturally introduces some errors, which might exceed the internal error of the scanner instrument. In addition, the targets must be kept stable during the whole scanning campaign. This might be inconvenient with the scanning works stretching over more than one day. On the other hand, target-based registration techniques can provide immediate georeferencing to an object coordinate system.

Surface-based registration techniques stand as efficient and versatile alternative to the target-based techniques. They simply bring the strenuous additional fieldwork of the registration task to the computer in the office while optimizing the project cost and duration and achieving a better accuracy. However, they do not provide the georeferencing option.

This work proposes a method which combines the advantageous parts of both techniques based on the least squares matching framework. The proposed method is a (truly) simultaneous one step solution for the matching and georeferencing of multiple 3D surfaces with their intensity information. The mathematical model is a hybrid system which contains different type of observations. The proposed method is an algorithmic extension of our previous work given in Gruen and Akca (2005) and Akca (2007). It generalizes the 3D surface matching problem in the sense that multiple 3D surfaces with their intensity information are globally matched and simultaneously georeferenced. Multiple primitives, surface information (geometry and intensity) and the (reference) point features, are co-registered together.

2. MATHEMATICAL MODELLING

2.1 Least Squares Multiple 3D Surface Matching

Assume a set of n surfaces of an object: $g_1(x, y, z)$,…, $g_n(x, y, z)$. The object is defined in a 3D Cartesian coordinate system, whereas the n surfaces are located in arbitrary local coordinate systems. The n surfaces are discrete 3D approximations of continuous functions of the object surface. They are digitized according to a sampling principle. The surface representation is carried out in a piecewise form, individually for each surface. $g_i(x, y, z)$ stands for any element of the i-th surface in this representation.

There are m mutual spatial overlaps between the surfaces $g_i(x, y, z)$. Every overlap satisfies a pairwise matching:

$$g_i(x,y,z) - e_i(x,y,z) = g_j(x,y,z) \quad , \quad i,j = 1,\dots,n \quad , \quad i \neq j \tag{1}$$

where $e_i(x, y, z)$ is a true error vector. It is assumed that i-th surface's noise is independent of j-th one. In order to prevent duplication, Equations (1) are written for every possible i-j pair with $i<j$.

Equations (1) are considered as nonlinear observation equations which model the observation vector $g_i(x, y, z)$ with functions $g_j(x, y, z)$. The Least Squares matching of the j-th surface to the i-th one is to be satisfied while the i-th surface is also subject to a 3D transformation (with respect to a predefined datum). This is the 3D analogy of the X-Y constraint version (i.e. grid sampling mode) of the multiphoto geometrically constrained matching (MPGC) (Gruen and Baltsavias, 1987) where both the template and the search image patches are transformed.

Both surfaces are transformed to an object coordinate system while minimizing a goal function, which measures the sum of the squares of the Euclidean distances between them. The geometric relationships are established via 7-parameter similarity transformations. They can be replaced by another type if needed.

Each surface is associated with a set of 3D similarity transformation parameters,

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix}_i = \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix}_i + m_i \mathbf{R}_i \begin{bmatrix} x_0 \\ y_0 \\ z_0 \end{bmatrix}_i \tag{2}$$

where $\mathbf{R}_i = \mathbf{R}_i(\omega, \varphi, \kappa)$ is the orthogonal rotation matrix, $[t_x \;\; t_y \;\; t_z]_i^{\mathrm{T}}$ is the translation vector, m_i is the uniform scale factor, and $(x_0, y_0, z_0)_i$ stand for the initial location of the surface.

Because Equations (1) are nonlinear, they are linearized by Taylor series expansion.

$$\begin{aligned} -e_i(x,y,z) = g_j^0(x,y,z) &+ \frac{\partial g_j^0(x,y,z)}{\partial x_j} \mathrm{d}x_j + \frac{\partial g_j^0(x,y,z)}{\partial y_j} \mathrm{d}y_j + \frac{\partial g_j^0(x,y,z)}{\partial z_j} \mathrm{d}z_j \\ - g_i^0(x,y,z) &- \frac{\partial g_i^0(x,y,z)}{\partial x_i} \mathrm{d}x_i - \frac{\partial g_i^0(x,y,z)}{\partial y_i} \mathrm{d}y_i - \frac{\partial g_i^0(x,y,z)}{\partial z_i} \mathrm{d}z_i \end{aligned} \tag{3}$$

dx, dy and dz are the differentiations of the selected 3D transformation model in Equation (2):

$$\begin{aligned} \mathrm{d}x &= \mathrm{d}t_x + a_{10}\,\mathrm{d}m + a_{11}\,\mathrm{d}\omega + a_{12}\,\mathrm{d}\varphi + a_{13}\,\mathrm{d}\kappa \\ \mathrm{d}y &= \mathrm{d}t_y + a_{20}\,\mathrm{d}m + a_{21}\,\mathrm{d}\omega + a_{22}\,\mathrm{d}\varphi + a_{23}\,\mathrm{d}\kappa \\ \mathrm{d}z &= \mathrm{d}t_z + a_{30}\,\mathrm{d}m + a_{31}\,\mathrm{d}\omega + a_{32}\,\mathrm{d}\varphi + a_{33}\,\mathrm{d}\kappa \end{aligned} \tag{4}$$

with a_{pq} as the coefficient terms.

Using the notation

$$g_x = \frac{\partial g^0(x,y,z)}{\partial x}, \quad g_y = \frac{\partial g^0(x,y,z)}{\partial y}, \quad g_z = \frac{\partial g^0(x,y,z)}{\partial z} \tag{5}$$

and substituting Equations (4), Equation (3) results in:

$$\begin{aligned}
-e_i(x,y,z) = {} & g_{xj}\,\mathrm{d}t_{xj} + g_{yj}\,\mathrm{d}t_{yj} + g_{zj}\,\mathrm{d}t_{zj} \\
& + (g_{xj}a_{10} + g_{yj}a_{20} + g_{zj}a_{30})\,\mathrm{d}m_j + (g_{xj}a_{11} + g_{yj}a_{21} + g_{zj}a_{31})\,\mathrm{d}\omega_j \\
& + (g_{xj}a_{12} + g_{yj}a_{22} + g_{zj}a_{32})\,\mathrm{d}\varphi_j + (g_{xj}a_{13} + g_{yj}a_{23} + g_{zj}a_{33})\,\mathrm{d}\kappa_j \\
& - g_{xi}\,\mathrm{d}t_{xi} - g_{yi}\,\mathrm{d}t_{yi} - g_{zi}\,\mathrm{d}t_{zi} \\
& - (g_{xi}b_{10} + g_{yi}b_{20} + g_{zi}b_{30})\,\mathrm{d}m_i - (g_{xi}b_{11} + g_{yi}b_{21} + g_{zi}b_{31})\,\mathrm{d}\omega_i \\
& - (g_{xi}b_{12} + g_{yi}b_{22} + g_{zi}b_{32})\,\mathrm{d}\varphi_i - (g_{xi}b_{13} + g_{yi}b_{23} + g_{zi}b_{33})\,\mathrm{d}\kappa_i \\
& - (g_i^0(x,y,z) - g_j^0(x,y,z))
\end{aligned} \tag{6}$$

where a_{pq} and b_{pq} are the coefficient terms for the differentiation of the transformation equations of the i-th and j-th surface, respectively. The terms g_x, g_y and g_z are the numerical derivatives of the object surface function $g(x, y, z)$. They are defined as the elements of the local surface normal vectors at the exact surface correspondence locations (Gruen and Akca, 2005). The linearized observation Equations (6) are written for each element of the i-th surface.
Equations (6) result in the following linear systems in matrix/vector form

$$\begin{aligned}
-\boldsymbol{e}_1 &= \mathbf{A}_1\boldsymbol{x} - \boldsymbol{l}_1 \quad , \quad \mathbf{P}_1 \\
-\boldsymbol{e}_2 &= \mathbf{A}_2\boldsymbol{x} - \boldsymbol{l}_2 \quad , \quad \mathbf{P}_2 \\
&\ \ \vdots \qquad \vdots \\
-\boldsymbol{e}_m &= \mathbf{A}_m\boldsymbol{x} - \boldsymbol{l}_m \quad , \quad \mathbf{P}_m
\end{aligned} \tag{7}$$

Equations (7) consist of m groups of observation equations. They can be combined in one sub-system as

$$-\boldsymbol{e} = \mathbf{A}\boldsymbol{x} - \boldsymbol{l} \quad , \quad \mathbf{P} \tag{8}$$

where $\mathbf{A}$ is the design matrix, $\boldsymbol{x}$ is the parameter vector which contains n sets of transformation parameters, $\mathbf{P} = \mathbf{P}_{ll}$ is the a priori weight matrix, $\boldsymbol{l} = g_i^0(x, y, z) - g_j^0(x, y, z)$ is the discrepancies vector that consists of the Euclidean distances between the corresponding elements of the overlapping surfaces. The calculation of the discrepancy vector $\boldsymbol{l}$ and the numerical derivative terms g_x, g_y and g_z requires an appropriate correspondence search procedure (Akca and Gruen, 2005).
Provided that $m \geq n$ is satisfied, the sub-system (of the design matrix) consisting of m Equations (7) implicitly contains the multiple overlap conditions. The normal equation matrix explicitly shows all the spatial relationships by non-zero off-diagonal elements.
With the statistical expectation operator E{ }, it is assumed that

$$\mathrm{E}\{\boldsymbol{e}\} = 0 \quad , \quad \mathrm{E}\{\boldsymbol{e}\boldsymbol{e}^{\mathrm{T}}\} = \sigma_0^2\mathbf{P}_{ll}^{-1} \tag{9}$$

The parameters are introduced into the system as observables with the associated weight coefficient matrix $\mathbf{P}_b$ as

$$-\boldsymbol{e}_b = \mathbf{I}\boldsymbol{x} - \boldsymbol{l}_b \quad , \quad \mathbf{P}_b \tag{10}$$

where $\mathbf{I}$ is the identity matrix and $\boldsymbol{l}_b$ is the (fictitious) observation vector. The weight matrix $\mathbf{P}_b$ has to be chosen appropriately, considering a priori information of the parameters.

2.2 The Generalized Model with Intensity Matching and Georeferencing

When some surfaces lack sufficient geometric information, their intensity information, if available, is introduced to the system. The intensity information is used to form quasisurfaces in addition to the actual ones. The formation of quasisurfaces is given in Akca (2007). The quasisurfaces are treated like actual surfaces in the estimation model. They contribute observation equations to the design matrix, joining the system by the same set of transformation parameters

$$-\boldsymbol{e}_c = \mathbf{A}_c \boldsymbol{x} - \boldsymbol{l}_c \quad , \quad \mathbf{P}_c \tag{11}$$

where $\boldsymbol{e}_c$, $\mathbf{A}_c$ and $\mathbf{P}_c$ are the true error vector, the design matrix, and the associated weight coefficient matrix for the quasisurface observations, respectively, and $\boldsymbol{l}_c$ is the constant vector that contains the Euclidean distances between the corresponding quasisurface elements.

Reference points whose coordinates are defined in an external (object) coordinate system, which are imaged in additional intensity images, or can be located in the pointclouds, serve as the fourth type of observations. They are formulated as 3D similarity transformations from local pointcloud systems to the object coordinate system in linearized matrix form

$$-\boldsymbol{e}_d = \mathbf{A}_d \boldsymbol{x} - \boldsymbol{l}_d \quad , \quad \mathbf{P}_d \tag{12}$$

where $\mathbf{A}_d$ is the design matrix, $\mathbf{P}_d$ is the associated weight matrix, and $\boldsymbol{l}_d$ is the discrepancies vector which contains the coordinate value differences of the reference points between the transformed local system and object coordinate system. At least 7 coordinate elements of 3 control points are needed for georeferencing.

Actually, the coordinates of the control points are not error-free quantities. In a strict model, they are treated as observations with their associated weight matrices as

$$-\boldsymbol{e}_e = \mathbf{A}_e \boldsymbol{x} - \boldsymbol{l}_e \quad , \quad \mathbf{P}_e \tag{13}$$

where $\mathbf{A}_e$, $\boldsymbol{x}$, and $\mathbf{P}_e$ are the design matrix, the parameter vector, and the associated weight coefficient matrix for the observations of the control point coordinates, respectively, and $\boldsymbol{l}_e$ is the discrepancy vector that contains the differences between the observed and estimated coordinate values. Here, the vector $\boldsymbol{x}$ is extended to include the *x-y-z* coordinate values of the control points in addition to the transformation parameters.

Equations (12) eliminate the datum deficiency existing in Equations (8). Alternatively, the datum constraints can be imposed by fixing the minimal number of parameters in Equations (10).

The hybrid system of Equations (8), (10), (11), (12) and (13) is of the combined adjustment type that allows simultaneous matching of geometry and intensity and additionally georeferencing of multiple 3D surfaces. The Least Squares solution of the system gives the solution vector as

$$\begin{aligned}\hat{\boldsymbol{x}} = (\mathbf{A}^{\mathrm{T}}\mathbf{P}\mathbf{A} + \mathbf{P}_b + \mathbf{A}_c^{\mathrm{T}}\mathbf{P}_c\mathbf{A}_c + \mathbf{A}_d^{\mathrm{T}}\mathbf{P}_d\mathbf{A}_d + \mathbf{A}_e^{\mathrm{T}}\mathbf{P}_e\mathbf{A}_e)^{-1} \\ (\mathbf{A}^{\mathrm{T}}\mathbf{P}\boldsymbol{l} + \mathbf{P}_b\boldsymbol{l}_b + \mathbf{A}_c^{\mathrm{T}}\mathbf{P}_c\boldsymbol{l}_c + \mathbf{A}_d^{\mathrm{T}}\mathbf{P}_d\boldsymbol{l}_d + \mathbf{A}_e^{\mathrm{T}}\mathbf{P}_e\boldsymbol{l}_e)\end{aligned} \tag{14}$$

and the variance factor as

$$\hat{\sigma}_0^2 = \frac{\boldsymbol{v}^{\mathrm{T}}\mathbf{P}\boldsymbol{v} + \boldsymbol{v}_b^{\mathrm{T}}\mathbf{P}_b\boldsymbol{v}_b + \boldsymbol{v}_c^{\mathrm{T}}\mathbf{P}_c\boldsymbol{v}_c + \boldsymbol{v}_d^{\mathrm{T}}\mathbf{P}_d\boldsymbol{v}_d + \boldsymbol{v}_e^{\mathrm{T}}\mathbf{P}_e\boldsymbol{v}_e}{r} \tag{15}$$

where r is the system redundancy, $\boldsymbol{v}$, $\boldsymbol{v}_b$, $\boldsymbol{v}_c$, $\boldsymbol{v}_d$ and $\boldsymbol{v}_e$ are residual vectors for actual surface observations, parameter observations, quasisurface observations, reference point observations (for georeferencing) and control point coordinate observations, respectively.

The solution is iterative. At the end of each iteration all surfaces are transformed to their new states using the updated sets of transformation parameters, and the design matrices and discrepancy vectors are re-evaluated. The iteration stops if each element of the alteration vector in Equation (14) falls below a certain limit.

The estimation model is the Generalized Gauss-Markoff, which can accommodate any kind of functional constraint flexibly, e.g. concentric scans, certain rotational differences, parallel or perpendicular objects in the pointcloud data, etc.

3. EXPERIMENTAL RESULTS

Because of the 125 anniversary of the construction of the Gotthard Tunnel (Switzerland), Credit Suisse has decided to have an exhibition in Zurich about the life and person of Alfred Escher (1819-1882), Swiss politician, promoter of the Gotthard Tunnel, railroad entrepreneur, and founder of Credit Suisse as well as of ETH Zurich.

In Zurich, there is a monument of Alfred Escher, which is located in front of the main railway station and is approximately 5 meter in high (9.5 meter considering also the basement). The goal of the project is the production of ten physical replicas of the Escher monument, starting from a 3D computer model.

The digitization was done with a Faro LS880 HE80 laser scanner, placed on a cherry picker (Figure 1). Totally 36 scans were acquired during two nights of on-site work. The data set contains approximately 4.4 million points with an average point spacing of 5-10 millimetres.

Figure 1. Pointcloud acquisition by laser scanning of the Alfread Escher statue on a cherry picker.

The proposed algorithm was used for the co-registration of the point clouds. Only the surface geometry and parameter observations were used. The example does not include the geo-referencing and intensity matching extensions.

At the first step, 3-5 tie points per pointcloud were interactively measured. Initial approximations were calculated by use of the tie point coordinates in a chained 3D similarity transformation. The first pointcloud was defined as the datum by fixing its parameters to a unit transformation with zero translation and rotation elements.

The transformation parameters of the all pointclouds were simultaneously calculated with sigma naught = 2.7 mm for the accuracy of the surface observations. Any surface correspondence

whose Euclidean distance exceeds 6 times the current sigma naught value was excluded from the design matrix. The final iteration of the adjustment used 20,442,040 surface correspondences. A high noise level in the data slowed down the convergence to 16 iterations.
The computation lasted more than 18 hours processing time on a laptop computer with Intel dual-core 2.16 GHz CPU and 2 GB physical memory. The main reason is the file-access oriented design of our software implementation. The file access for reading and writing is within a few milliseconds, while the memory access is within some nanoseconds. On the other hand, the memory request of the software has never exceeded 300 MB during the entire calculation.
Our software implementation loads at maximum two pointclouds into the memory at any instant of (processing) time. All the information, e.g. 3D coordinates, correspondences, elements of the 3D boxing for the space partitioning, etc. are kept in the files whose contents are loaded into memory only when needed.

Figure 2. (Left) The final 3D model of the Alfred Escher statue, (right) still incomplete physical replica of the Alfred Escher monument (the missing parts are attached later).

After the co-registration step, all pointclouds were merged, filtered for noise reduction, sub-sampled and triangulated for surface generation. The 3D modelling operations were carried out using Geomagic Studio 9. Note that no editing has been made on the final model, except for the cropping of the area of interest (Figure 2). An edited version of the 3D model was used for the replica production. Ten replicas were produced at a scale 1:2 (Figure 2).

4. CONCLUSIONS

A method for the simultaneous co-registration of multiple 3D pointclouds is presented. It is capable of georeferencing as well as matching of the intensity information when some parts of the object surface lack sufficient geometry information. The estimation model is the Generalized Gauss-Markoff which allows any kind of object space conditions to be formulated as functional constraints, e.g. co-centric scans, perpendicular or parallel objects in the pointclouds, etc.

A practical experiment shows the capability of the method. A successful solution has been achieved. However, the computation time is the main burden. A more efficient software implementation and a multi-resolution approach during the iterations can accelerate the procedure substantially. The future work will also include experimentations with the georeferencing and intensity matching approaches.

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