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A NEW ALGORITHM FOR 3D SURFACE MATCHING

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ABSTRACT:

A new algorithm for least squares matching of overlapping 3D surfaces, digitized/sampled point by point using a laser scanner device, the photogrammetric method or other techniques, is proposed. In photogrammetry, the problem statement of surface patch matching and its solution method was first addressed by Gruen (1985a) as a straight application of Least Squares Matching. There have been some studies on the absolute orientation of stereo models using DEMs as control information. These works have been known as *DEM matching*. Furthermore, techniques for 2.5D DEM surface matching have been developed, which correspond mathematically with least squares image matching. 2.5D surfaces have limited value, especially in close range applications. Our proposed method estimates the transformation parameters between two or more fully 3D surface patches, minimizing the Euclidean distances instead of Z-differences between the surfaces by least squares. This formulation gives the opportunity of matching arbitrarily oriented surface patches. An observation equation is written for each surface element on the template surface patch, i.e. for each sampled point. The geometric relationship between the conjugate surface patches is defined as a 7-parameter 3D similarity transformation. The Least Squares observations of the adjustment are defined by the observation vector whose elements are Euclidean distances between the template and search surface elements. The unknown transformation parameters are treated as stochastic quantities using proper weights. This extension of the functional model gives control over the estimation parameters. The details of the mathematical modelling of the proposed method, the convergence behavior, and statistical analysis of the theoretical precision of the estimated parameters are explained. Furthermore, some experimental results based on registration of close-range laser scanner and photogrammetric point clouds are presented. This new surface matching technique derives its mathematical strength from the least squares image matching concept and offers high level flexibility for any kind of 3D surface correspondence problem, as well as statistical tools for the analysis of the quality of the final results.

1. INTRODUCTION

Laser scanners can measure directly 3D coordinates of huge amounts of points in a short time period. Since the laser scanner is a line-of-sight instrument, in many cases the object has to be scanned from different viewpoints in order to completely reconstruct it. Because each scan has its own local coordinate system, all the local point clouds must be transformed into a common coordinate system. This procedure is usually referred to as registration. Actually the registration is not a specific problem to the laser scanner domain. Since the problem is more general than the given definition, the emphasis of our work is to investigate the most general solution of the registration problem on a theoretical basis.

In the past, several efforts have been made concerning the registration of 3D point clouds, especially in the Computer Vision area. One of the most popular methods is the Iterative Closest Point (ICP) algorithm developed by Besl and McKay (1992), Chen and Medioni (1992), and Zhang (1994). The ICP is based on the search of pairs of nearest points in the two sets, and estimating the rigid transformation, which aligns them. Then, the rigid transformation is applied to the points of one set, and the procedure is iterated until convergence. The ICP assumes that one point set is a subset of the other. When this assumption is not valid, false matches are created, that negatively influence the convergence of the ICP to the correct solution (Fusiello et al., 2002). Several variations and improvements of the ICP method have been made (Masuda and Yokoya, 1995, Bergevin et al., 1996), but several problems still remain. From a computational expense point of view it is highly time consuming due to the exhaustive search for the nearest point (Sequeira, et al., 1999). Another problem is that it requires every point in one surface to have a corresponding point on the other surface. An alternative approach to this search problem was proposed by Chen and Medioni (1992). They used the distance between the surfaces in the direction normal to the first surface as a registration evaluation function instead of point–to–nearest point distance. This idea was originally proposed by Potmesil (1983). In (Dorai et al., 1997) the method of Chen and Medioni was extended to an optimal weighted least-squares framework. Zhang (1994) proposed a thresholding technique using robust statistics to limit the maximum distance between points. Masuda and Yokoya (1995) used the ICP with random sampling and least median square error measurement that is robust to a partially overlapping scene. Okatani and Deguchi (2002) propose the best transformation of two range images to align each other by taking into account the measurement error properties, which are mainly dependent on both the viewing direction and the distance to the object surface. The ICP algorithm always converges monotonically to a local minimum with respect to the mean-square distance objective function (Besl and McKay, 1992). Even if good initial approximations for the transformation parameters are provided, in some cases it might converge to a wrong solution due to its closest point (or tangent plane) search scheme. It does not use the local surface gradients in order to direct the solution to a global minimum. Another deficiency of the ICP method is to be not able to handle multi-scale range data. Several reviews and comparison studies about the ICP variant methods are available in the literature (Jokinen and Haggren, 1998, Williams et al., 1999, Campbell and Flynn, 2001).

Since 3D point clouds derived by any method or device represent the object surface, the problem should be defined as a surface matching problem. In Photogrammetry, the problem statement of surface patch matching and its solution method was first addressed by Gruen (1985a) as a straight extension of Least Squares Matching (LSM).

There have been some studies on the absolute orientation of stereo models using DEMs as control information. This work is known as *DEM matching*. The absolute orientation of the models using DTMs as control information was first proposed by Ebner and Mueller (1986), and Ebner and Strunz (1988). Afterwards, the functional model of DEM matching has been formulated by Rosenholm and Torlegard (1988). This method basically estimates the 3D similarity transformation parameters between two DEM patches, minimizing the least square differences along the Z axes. Several applications of DEM matching have been reported (Karras and Petsa, 1993, Pilgrim, 1996, Mitchell and Chadwick, 1999, Xu and Li, 2000). Maas (2000) successfully applied a similar method to register airborne laser scanner strips, among which vertical and horizontal discrepancies generally show up due to GPS/INS accuracy problems. Another similar method has been presented for registering surfaces acquired using different methods, in particular, laser altimetry and photogrammetry (Postolov, Krupnik, and McIntosh, 1999). Furthermore, techniques for 2.5D DEM surface matching have been developed, which correspond mathematically with Least Squares Image Matching. The DEM matching concept can only be applied to 2.5D surfaces, whose analytic function is described in the explicit form, i.e. z = f(x,y). Of course, this formulation has several problems in the matching of solid (3D) surfaces.

Although the registration of 3D point clouds is a very active research area in both Computer Vision and Photogrammetry, there is not such a method that has a complete capability to the following three properties: matching of multi-scale data sets, matching of real 3D surfaces without any limitation, fitting the physical reality of the problem statement as good as possible. The proposed work completely meets these requirements.

The Least Squares Matching concept had been applied to many different types of measurement and feature extraction problems due to its high level of flexibility and its powerful mathematical model: Adaptive Least Squares Image Matching (Gruen, 1984, Gruen, 1985a), Geometrically Constrained Multiphoto Matching (Gruen and Baltsavias, 1988), Image Edge Matching (Gruen and Stallmann, 1991), Multiple Patch Matching with 2D images (Gruen, 1985b), Multiple Cuboid (voxel) Matching with 3D images (Maas, 1994, Maas and Gruen, 1995), Globally Enforced Least Squares Template Matching (Gruen and Agouris, 1994), Least Squares B-spline Snakes (Gruen and Li, 1996). For a detailed survey the author refers to (Gruen, 1996). If 3D point clouds derived by any device or method represent an object surface, the problem should be defined as a surface matching problem instead of the 3D point cloud matching. In particular, we treat it as least squares matching of overlapping 3D surfaces, which are digitized/sampled point by point using a laser scanner device, the photogrammetric method or other surface measurement techniques. This definition allows us to find a more general solution for the problem as well as to establish a mathematical model in the context of LSM.

Our proposed method, Least Squares 3D Surface Matching (LS3D), estimates the 3D transformation parameters between two or more fully 3D surface patches, minimizing the Euclidean distances between the surfaces by least squares. This formulation gives the opportunity of matching arbitrarily oriented 3D surface patches. An observation equation is written for each surface element on the template surface patch, i.e. for each sampled point. The geometric relationship between the conjugate surface patches is defined as a 7-parameter 3D similarity transformation. This parameter space can be extended or reduced, as the situation demands it. The constant term of the adjustment is given by the observation vector whose elements are Euclidean distances between the template and search surface elements. Since the functional model is non-linear, the solution is iteratively approaching to a global minimum. The unknown transformation parameters are treated as stochastic quantities using proper weights. This extension of the mathematical model gives control over the estimation parameters. The details of the mathematical modeling of the proposed method, the convergence behaviour, and the statistical analysis of the theoretical precision of the estimated parameters are explained in the following section. The experimental results based on registration of close-range laser scanner and photogrammetric point clouds are presented in the third section. The conclusions are given in the last section.

2. LEAST SQUARES 3D SURFACE MATCHING

2.1 The Estimation Model

Assume that two different surfaces of the same object are digitized/sampled point by point, at different times (temporally) or from different viewpoints (spatially). f(x,y,z) and g(x,y,z) are conjugate regions of the object in the *left* and *right* surfaces respectively. The problem statement is finding the correspondent part of the *template* surface patch f(x,y,z) on the *search* surface g(x,y,z).

$$f(x,y,z) = g(x,y,z) \tag{1}$$

According to Equation (1) each surface element on the template surface patch f(x,y,z) has an exact correspondent surface element on the search surface patch g(x,y,z), if both of the surface patches would be continuous surfaces. In order to model the random errors, which come from the sensor, environmental conditions or measurement method, a true error vector e(x,y,z) has to be added.

$$f(x,y,z) - e(x,y,z) = g(x,y,z) \tag{2}$$

The matching is achieved by minimizing a goal function, which measures the Euclidean distances between the template and the search surface elements. Equation (2) is considered observation equations, which functionally relate the observations f(x,y,z) to the parameters of g(x,y,z). The final location is estimated with respect to an initial position of g(x,y,z), the approximation of the conjugate search surface patch $g^0(x,y,z)$.

To express the geometric relationship between the conjugate surface patches, a 7-parameter 3D similarity transformation is used. Depending on the deformation between the template and the search surfaces, the geometric relationship could be defined using any other type of 3D transformation methods, e.g. 12-parameter affine, 24-parameter tri-linear, or 30-parameter quadratic family of transformations.

$$\begin{aligned} x &= t_x + m(r_{11}x_0 + r_{12}y_0 + r_{13}z_0) \\ y &= t_y + m(r_{21}x_0 + r_{22}y_0 + r_{23}z_0) \\ z &= t_z + m(r_{31}x_0 + r_{32}y_0 + r_{33}z_0) \end{aligned} \tag{3}$$

where $r_{ij} = R(\omega,\varphi,\kappa)$ are the elements of the orthogonal rotation matrix, $[t_x \ \ t_y \ \ t_z]^T$ is the translation vector, and m is the central dilation.

In order to perform least squares estimation, Equation (2) must be linearized by Taylor expansion, ignoring 2^{nd} and higher order terms.

$$f(x,y,z) - e(x,y,z) = g^0(x,y,z) + \frac{\partial g^0(x,y,z)}{\partial x}dx + \frac{\partial g^0(x,y,z)}{\partial y}dy + \frac{\partial g^0(x,y,z)}{\partial z}dz \quad (4)$$

where

$$dx = \frac{\partial x}{\partial p_i}dp_i \;\;,\;\; dy = \frac{\partial y}{\partial p_i}dp_i \;\;,\;\; dz = \frac{\partial z}{\partial p_i}dp_i \quad (5)$$

where $p_i \in \{t_x , t_y , t_z , m, \omega, \varphi, \kappa\}$ is the i-th transformation parameter in Equation (3). Differentiation of Equation (3) gives:

$$\begin{aligned} dx &= dt_x + a_{10}dm + a_{11}d\omega + a_{12}d\varphi + a_{13}d\kappa \\ dy &= dt_y + a_{20}dm + a_{21}d\omega + a_{22}d\varphi + a_{23}d\kappa \\ dz &= dt_z + a_{30}dm + a_{31}d\omega + a_{32}d\varphi + a_{33}d\kappa \end{aligned} \quad (6)$$

where a_{ij} are the coefficient terms. In the context of adjustment of observation equations, each measurement is related with the function whose variables are unknown parameters. This function constitutes the functional model of the whole mathematical model. In the following definition, the terms $\{g_x , g_y , g_z\}$ are 1st derivatives of this function, which is itself of the search surface patch g(x,y,z). In other words these terms are local surface gradients on the search surface. Using the following notation,

$$g_x = \frac{\partial g^0(x,y,z)}{\partial x} \;\;,\;\; g_y = \frac{\partial g^0(x,y,z)}{\partial y} \;\;,\;\; g_z = \frac{\partial g^0(x,y,z)}{\partial z} \quad (7)$$

and substituting Equations (6), Equation (4) gives the following equation:

$$\begin{aligned} -e(x,y,z) = {} & g_x dt_x + g_y dt_y + g_z dt_z + (g_x a_{10} + g_y a_{20} + g_z a_{30})dm + \\ & (g_x a_{11} + g_y a_{21} + g_z a_{31})d\omega + \\ & (g_x a_{12} + g_y a_{22} + g_z a_{32})d\varphi + \\ & (g_x a_{13} + g_y a_{23} + g_z a_{33})d\kappa - (f(x,y,z) - g^0(x,y,z)) \end{aligned} \quad (8)$$

In matrix notation

$$-\mathbf{e} = \mathbf{A}\,\mathbf{x} - \ell \quad , \quad \mathbf{P} \quad (9)$$

where $\mathbf{A}$ is the design matrix, $\mathbf{x}^T = [dt_x \; dt_y \; dt_z \; dm \; d\omega \; d\varphi \; d\kappa]$ is the parameter vector, and ℓ = f(x,y,z)–g^0(x,y,z) is the observation vector that consists of the Euclidean distances between the transformed point using current transformation parameters and its coincident surface element on the other surface. With the statistical expectation operator E{} and the assumptions

$$\mathbf{e} \sim N(0, \sigma_0^2 \mathbf{Q}_{ll}) \;\;,\;\; \sigma_0^2 \mathbf{Q}_{ll} = \sigma_0^2 \mathbf{P}_{ll}^{-1} = \mathbf{K}_{ll} = E\{\mathbf{e}\mathbf{e}^T\} \quad (10)$$

the system (9) and (10) is a Gauβ-Markov estimation model.

The unknown 3D similarity transformation parameters are treated as stochastic quantities using proper weights. This extension gives advantages of control over the estimating parameters (Gruen, 1986). In the case of poor initial approximations for unknowns or badly distributed 3D points along the principal component axes of the surface, some of the unknowns, especially the scale factor m, may converge to a wrong solution, even if the scale factors between the surface patches are same.

$$-\mathbf{e}_b = \mathbf{I}\,\mathbf{x} - \ell_b \quad , \quad \mathbf{P}_b \quad (11)$$

The least squares solution of the joint system Equations (9) and (11) gives the unbiased minimum variance estimation for the parameters

$$\hat{\mathbf{x}} = (\mathbf{A}^T\mathbf{P}\mathbf{A} + \mathbf{P}_b)^{-1}(\mathbf{A}^T\mathbf{P}\ell + \mathbf{P}_b\ell_b) \qquad \text{solution vector} \quad (12)$$

$$\hat{\sigma}_0^2 = \frac{\mathbf{v}^T\mathbf{P}\mathbf{v} + \mathbf{v}_b^T\mathbf{P}_b\mathbf{v}_b}{r} \qquad \text{variance factor} \quad (13)$$

$$\mathbf{v} = \mathbf{A}\,\hat{\mathbf{x}} - \ell \qquad \text{residual vector for surface observations} \quad (14)$$

$$\mathbf{v}_b = \mathbf{I}\,\hat{\mathbf{x}} - \ell_b \qquad \text{residual vector for additional observations} \quad (15)$$

where ^ stands for the Least Squares (LS) Estimator. The function values g(x,y,z) in Equation (2) are actually stochastic quantities. This fact is neglected here to allow the use of the Gauβ-Markov model and to avoid unnecessary complications, as typically done in LSM (Gruen, 1985a).

Since the functional model is non-linear, the solution iteratively approaches to a global minimum. In the first iteration the initial approximations for the parameters must be provided:

$$p_i^0 \in \{t_x^0, t_y^0, t_z^0, m^0, \omega^0, \varphi^0, \kappa^0\} \quad (16)$$

The iteration stops if each element of the alteration vector $\hat{\mathbf{x}}$ in Equation (12) falls below a certain limit:

$$|dp_i| < c_i \quad , \quad i = \{1,2,...,7\} \quad (17)$$

The theoretical precision of the estimated parameters can be evaluated by means of the covariance matrix

$$\mathbf{K}_{xx} = \hat{\sigma}_0^2 \mathbf{Q}_{xx} = \hat{\sigma}_0^2 \mathbf{N}^{-1} = \hat{\sigma}_0^2 (\mathbf{A}^T\mathbf{P}\mathbf{A} + \mathbf{P}_b)^{-1} \quad (18)$$

In a least squares adjustment of indirect observations whose functional model is non-linear, the 1st derivatives (2nd and higher order terms are generally neglected in the Taylor expansion) with respect to unknowns are very important terms, since they direct the estimation towards a global minimum. The terms $\{g_x , g_y , g_z\}$ are numeric derivatives of the unknown surface patch g(x,y,z). Its calculation depends on the analytical representation of the surface elements. As a first method, let us represent the search surface elements as plane surface patches, which are constituted by fitting a plane to 3 neighboring knot points, in the implicit form

$$g^0(x,y,z) = Ax + By + Cz + D = 0 \quad (19)$$

where A, B, C, and D are parameters of the plane. Using the mathematical definition of the derivation, the numeric 1st derivation according to the x-axis is

$$g_x = \frac{\partial g^0(x,y,z)}{\partial x} = \lim_{\Delta x \to 0} \frac{g^0(x+\Delta x,y,z) - g^0(x,y,z)}{\Delta x} \quad (20)$$

where the numerator term of the equation is simply the distance between the plane and the off-plane point (x+Δx,y,z). Then using the point-to-plane distance formula,

$$g_x = \frac{A(x+\Delta x) + By + Cz + D}{\Delta x \sqrt{A^2+B^2+C^2}} = \frac{A}{\sqrt{A^2+B^2+C^2}} \quad (21)$$

is obtained. Similarly g_y and g_z are calculated numerically.

$$g_y = \frac{B}{\sqrt{A^2+B^2+C^2}} \;\;,\;\; g_z = \frac{C}{\sqrt{A^2+B^2+C^2}} \quad (22)$$

Actually these numeric derivative values $\{g_x, g_y, g_z\}$ are x-y-z components of the local surface normal vector at that point.

$$\vec{n} = \frac{\vec{\nabla} g^0}{\left\| \vec{\nabla} g^0 \right\|} = \frac{\begin{bmatrix} \dfrac{\partial g^0}{\partial x} & \dfrac{\partial g^0}{\partial y} & \dfrac{\partial g^0}{\partial z} \end{bmatrix}^T}{\left\| \vec{\nabla} g^0 \right\|} = \frac{\begin{bmatrix} A & B & C \end{bmatrix}^T}{\sqrt{A^2 + B^2 + C^2}} \quad (23)$$

In the case of representation of search surface elements as parametric bi-linear surface patches, which are constituted by fitting the bi-linear surface to 4 neighboring knot points $P_{i,j}$:

$$\vec{G}(u,w) = \vec{P}_{0,0}(1-u)(1-w) + \vec{P}_{0,1}(1-u)w + \vec{P}_{1,0}u(1-w) + \vec{P}_{1,1}uw \quad (24)$$

where $u,w \in [0,1]^2$ and $G, P_{i,j} \in \mathcal{R}^3$. Again the numeric derivative terms $\{g_x, g_y, g_z\}$ are calculated from components of the local surface normal vector on the parametric bi-linear surface patch:

$$\vec{n} = \begin{bmatrix} g_x & g_y & g_z \end{bmatrix}^T = \frac{\vec{\nabla} G}{\left\| \vec{\nabla} G \right\|} = \frac{\dfrac{\partial \vec{G}(u,w)}{\partial u} \times \dfrac{\partial \vec{G}(u,w)}{\partial w}}{\left\| \vec{\nabla} G \right\|} \quad (25)$$

With this approach a better a posteriori sigma value could be obtained due to a smoothing effect. In the case of insufficient initial approximations, the numeric derivatives $\{g_x, g_y, g_z\}$ can be calculated on the template surface patch f(x,y,z) instead of on the search surface g(x,y,z) in order to speed-up the convergence.

2.2 Precision and Reliability Issues

The standard deviations of the estimated transformation parameters and the correlations between themselves may give useful information concerning the stability of the system and quality of the data content (Gruen, 1985a).

$$\hat{\sigma}_p = \hat{\sigma}_0 \sqrt{q_{pp}} \quad , \quad p_i \in \{t_x, t_y, t_z, m, \omega, \varphi, \kappa\} \ , \ q_{pp} \in \mathbf{Q}_{xx} \quad (26)$$

As pointed out in (Maas, 2000), the estimated standard deviations of the translation parameters are too optimistic due to stochastic properties of the search surface.

Because of the high level redundancy of a typical data arrangement, a certain amount of occlusions and/or outliers do not have significant effect on the estimated parameters. Baarda's data-snooping method can be favourably used to localize the occluded or gross erroneous measurements.

2.3 Computational Aspects

The computational complexity is of order $O(N^2)$, where N is the number of employed points in the matching process. The actual problem is to search the correspondent element of the template surface on the search surface patch, whereas the adjustment part is a small system, and can quickly be solved using back-substitution followed by Cholesky decomposition. Searching the correspondence is an algorithmic problem, and needs professional software optimization techniques and programming skills, which are not within the scope of this paper.

Since the method needs initial approximations of the unknowns due to the non-linear functional model, one of the methods for pre-alignment in the literature (Habib and Schenk, 1999, Murino et al., 2001, Lucchese et al., 2002, Vanden Wyngaerd and Van Gool, 2002) should be utilized.

Two 1st degree C^0 continuous surface representations are implemented, and explained in detail. In the case of multi-resolution data sets, in which point densities are significantly different on the template and search surface patches, higher degree C^1 continuous composite surface representations, e.g. bi-cubic Hermit surface (Peters, 1974), should give better results, of course increasing the computational expenses.

2.4 Convergence of Solution Vector

In a standard LS adjustment calculus in geodesy and photogrammetry, the function of the unknowns is unique, exactly known, and analytically continuous everywhere, e.g. the collinearity equations in the bundle adjustment. Here the function g(x,y,z) is discretized by using a definite sampling rate, which leads to slow convergence, oscillations, even divergence in some cases with respect to the standard adjustment. The convergence behaviour of the proposed method basically depends on the quality of the initial approximations and quality of the data content, and it usually achieves the solution after 4th or 5th iterations (Figure 1), as typically in LSM.

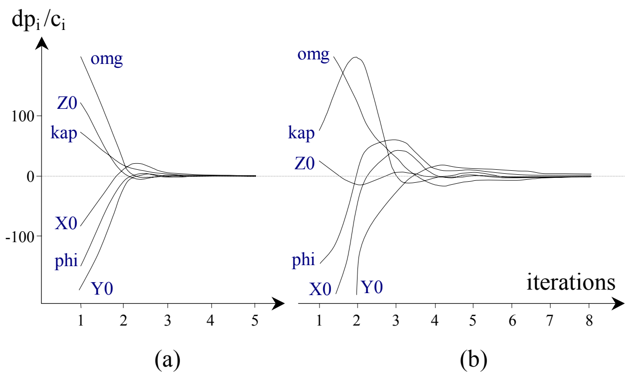


Figure 1: Typical examples for fast convergence (a) and slow convergence (b). Note that scale factor is fixed to unity.

3. THE EXPERIMENTAL RESULTS

Two practical examples are given to show the capabilities of the method. All experiments were carried out using own self-developed C/C++ software that runs on *Microsoft Windows®* OS. Processing times given in Table 1 were counted on such a PC, whose configuration is *Intel®* P4 2.53 GHz CPU, 1 GB RAM. The first example is the registration of three surface patches, which were photogrammetrically measured 3D point clouds of a human face from multi-images (Figure 2). For the mathematical and implementation details of this surface measurement method the author refers to (D'Apuzzo, 2002).

Left and right search surface patches (Figure 2-a and 2-c) were matched to the centre template surface patch (Figure 2-b) by use of LS3D. Since the data set already came in a common coordinate system, the rotation angles (ω,φ,κ) of the search surfaces were deteriorated by $\sim 10^g$ in the first iteration. Numerical results of the matching of the left surface and the right surface patches are given at parts I-L and I-R of Table 1 respectively. Relatively high standard deviations for the estimated t_x and φ (note that high physical correlation between x and φ due to a conventional axes configuration) exhibit the narrow overlapping area along the x-axis, nevertheless the matching result is successful. The estimated σ_0 values prove the accuracy potential of the surface measurement method, given as 0.2 mm by D'Apuzzo (2002).

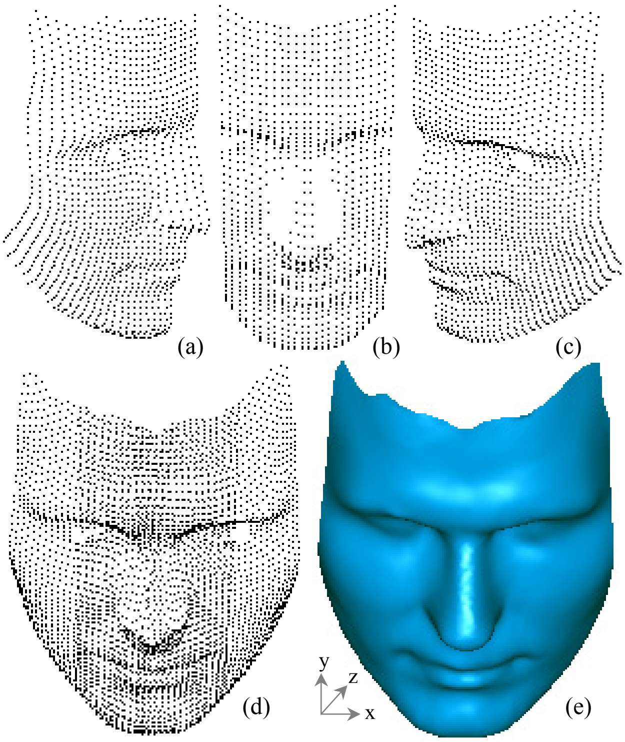


Figure 2: (a) left-search surface, (b) centre-template surface, (c) right-search surface, (d) obtained 3D point cloud after LS3D surface matching, (e) shaded view of the final composite surface.

The second experiment refers to the matching of two overlapping 3D point clouds (Figure 3), which are a part of a chapel in Wangen, Germany, and were scanned using IMAGER 5003 terrestrial laser scanner (Zoller+Fröhlich). Initial approximations of the unknowns were provided by interactively selecting 3 common points on the both surfaces before the matching. Obtained results are given at part II of Table 1. The estimated σ_0 gives valuable information about the sensor noise level and the accuracy limit of the scanner as >1.7 mm.

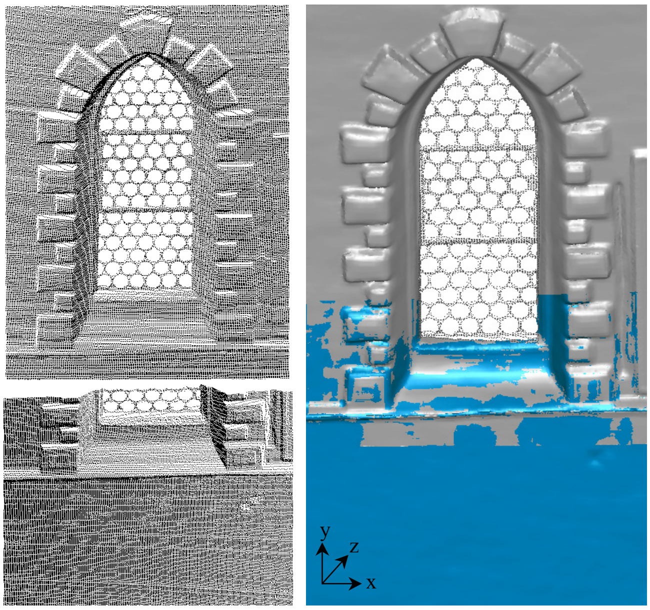
Table 1: Experimental results

	s	n	i	t	d	$\hat{\sigma}_0$	$\hat{\sigma}_{tx} / \hat{\sigma}_{ty} / \hat{\sigma}_{tz}$	$\hat{\sigma}_{\omega} / \hat{\sigma}_{\varphi} / \hat{\sigma}_{\kappa}$
				sec	mm	mm	mm	c
I-L	P	2497	7	0.6	1.5	0.19	0.15/0.07/0.05	0.96/2.44/1.90
	B		7	1.3		0.19	0.15/0.07/0.05	0.96/2.42/1.91
I-R	P	3285	6	0.5	1.5	0.21	0.13/0.03/0.05	0.68/2.25/1.73
	B		6	1.4		0.21	0.13/0.03/0.05	0.69/2.26/1.75
II	P	13461	5	3.8	10	1.74	0.23/0.62/0.01	0.69/0.17/0.46
	B		4	5.6		1.72	0.22/0.61/0.01	0.69/0.17/0.46

I-L: left face surface , I-R: right face surface, II: laser scanner data
s: surface representation, P: plane, B: bi-linear surface, n: number of employed points, i: iterations, t: process time, d: ~ point spacing

The parametric bi-linear surface representation gives a slightly better convergence rate and a better a posteriori sigma value than the triangle plane representation, while increasing the computational expenses. The standard deviation of the z-component of the translation vector shows the excellent data content in the depth direction, but the relative precision is highly optimistic, which is ~1/1000 of the point spacing.

Since LS3D reveals the sensor noise level and accuracy potential of any kind of surface measurement method or device, it should be used for comparison and validation studies.



(a) (b)

Figure 3: (a) top - template surface patch, (a) bottom - search surface patch, (b) overlay of the shaded surfaces.

4. CONCLUSIONS

LSM is a fundamental measurement algorithm, and has been applied to a great variety of data matching problems due to its strong mathematical model. Two well-known ones are LS image matching in 2D pixel space, and LS multiple cuboid matching in 3D voxel space. The LS3D is bridging the conceptual gap between the LS image matching and the LS cuboid matching.

This new 3D surface matching technique is a generalization of the least squares 2D image matching concept and offers high flexibility for any kind of 3D surface correspondence problem, as well as monitoring capabilities for the analysis of the quality of the final results by means of precision and reliability criterions. Another powerful aspect of this proposed method is its ability to handle multi-resolution, multi-temporal, multi-scale, and multi-sensor data sets. The technique can be applied to a great variety of data co-registration problems. In addition time dependent (temporal) variations of the object surface can be inspected, tracked, and localized using the statistical analysis tools of the method.

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