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Multi-sensor calibration through iterative registration and fusion

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ABSTRACT

In this paper, a new multi-sensor calibration approach, called *iterative registration and fusion (IRF)*, is presented. The key idea of this approach is to use surfaces reconstructed from multiple point clouds to enhance the registration accuracy and robustness. It calibrates the relative position and orientation of the spatial coordinate systems among multiple sensors by iteratively registering the discrete 3D sensor data against an evolving reconstructed B-spline surface, which results from the Kalman filter-based multi-sensor data fusion. Upon each registration, the sensor data gets closer to the surface. Upon fusing the newly registered sensor data with the surface, the updated surface represents the sensor data more accurately. We prove that such an iterative registration and fusion process is guaranteed to converge. We further demonstrate in experiments that the IRF can result in more accurate and more stable calibration than many classical point cloud registration methods.

1. Introduction

Multiple sensors of various modalities and with different sensing resolutions, measurement ranges and uncertainties are increasingly being integrated into one platform to improve the overall sensing speed and coverage, and to reduce the uncertainty. Such multi-sensor systems have found a wide range of applications in terrain surveillance, military reconnaissance, dimensional metrology and shape digitization in reverse engineering [1,11,19,24].

In order to effectively integrate and fuse spatial data from different 3D sensors, it is important to know the relative position and orientation of the spatial coordinate systems among these sensors [2,8]. The calibration of such spatial relationships among different sensors can be broken down into two tasks: intrinsic calibration where internal sensor parameters are determined and extrinsic calibration where the position and the orientation of a sensor relative to a given coordinate system are determined. In this paper, we assume the intrinsic calibration has been properly conducted and we focus on the extrinsic calibration. Among many methods for extrinsic calibration [3,5,9,28,42], sensor data registration through the iterative closest point (ICP) method or its variants is a common choice [3,4,28] since it requires neither precise knowledge of the geometry of the calibration artifacts nor explicit data correspondence from different sensor data.

However, the calibration result from such a point based registration method is affected by the amount of sensor data and the level of data noise. This problem becomes especially severe in a multi-sensor platform where data density and variance from different sensors vary significantly.

In order to ensure accurate and robust calibration of multiple sensors, in this paper, we present a new approach for multi-sensor calibration. The basis of our approach is two-fold: (a) a continuous surface reconstructed from the sensor data provides a more accurate geometry for data registration than the discrete point cloud and (b) the surface reconstructed from multiple sensor data is more accurate than that from any single sensor data. We call our approach *iterative registration and fusion* (IRF). The core idea of the IRF is to iterate the following two steps:

1. Using the ICP algorithm [3] to register different sensor data against a reconstructed surface to achieve accurate and robust alignment for the ensuing point–surface fusion.
2. Using the Kalman filter to fuse the newly aligned sensor data with the previously reconstructed surface to obtain an updated, accurate surface for the subsequent point–surface registration.

The main contribution of this paper is the following.

- We develop a new approach, IRF, for aligning point cloud data of different sensor characteristics such as sampling density and uncertainty (variance). Compared with the original ICP algorithm [3] and its variants such as point–plane registration [5], the novelty of our approach lies in the use of an extra fusion process (the second step above) that generates a smooth surface from the aligned multi-sensor data for subsequent point–surface registration. Unlike typical point–surface registration [3,25] where a surface, often nominal, is given (e.g. measurement data points are to be

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aligned with the nominal shape model to determine the part shape deviation in metrology applications), the surface in IRF is reconstructed from the points and dynamically evolves as the registration process proceeds. We demonstrate that (a) point–surface registration based on the surface reconstructed from point clouds leads to more accurate registration than these ICP variants and (b) the IRF results in an even more accurate and robust registration.
- We extend the Kalman filter-based B-spline surface reconstruction [14,15,38] into the IRF process. More specifically, we develop a formulation that enables B-spline surface based data fusion, data withdrawal and data registration.
- We further prove and demonstrate that the IRF process is guaranteed to converge to a minimum error. This convergence property facilitates the selection of the initial surface model by checking the accuracy of the surface after the process is converged.

The remainder of this paper is organized as follows. Section 2 reviews prior work in sensor calibration and 3D data registration. Section 3 presents the mathematical formulations for surface-based data fusion, data withdrawal, and data registration. Section 4 describes the overall iterative registration and fusion method. Section 5 gives the experimental results. Section 6 discusses the convergence theorem and how IRF performs under different conditions. This paper concludes in Section 7.

2. Literature review

During the object digitization process, complex 3D objects often require sensing from multiple views or several sensors [2,31]. Multi-sensor calibration typically includes two steps: intrinsic calibration to determine each individual sensor's internal parameters [32,33] and data bias [12,13] and extrinsic calibration to determine the relative position and orientation between sensors [24]. In this paper, we concentrate on the extrinsic calibration among sensors.

Multiple methods are available for registering multi-view or multi-sensor data into one common coordinate system. Pair-wise data registration using point-to-point ICP has been widely used [3–5,9,20,21,28,29,41,42] and performs well under an appropriate initial orientation and with sufficient data density and low data noise. The algorithmic convergence of these variants is analyzed in [25]. Even though point–surface registration has been discussed in many of these approaches, they assume the surface is given.

Besides the pair-wise correspondence method based on closest points between two data sets, shape features such as spin images (oriented point-normal distribution) [16], linear features [35], integral volume descriptors [10], and invariant features (curvature, moment invariants, spherical harmonics invariants) [30] have also been extracted and used to build the optimal correspondence between a set of point clouds, and followed by the point-to-point ICP to obtain optimal registration.

Since the pair-wise registration for multi-view or multi-sensor data may result in the accumulation of registration error [2,8], methods have been proposed to improve the overall registration accuracy through a registration network of multi-view data error distribution [2,8], pair-wise alignment constraints [26], optimally distributing the error along the registration cycles [31], force-based optimization [7], and manifold optimization [18].

To get higher registration accuracy, a method combining surface reconstruction and registration is recently proposed in [44]. However, different noise levels are not considered in the surface reconstruction. In our approach, surface reconstruction is formulated as a multi-sensor data fusion process, and different noise levels are considered to obtain a more accurate fusion surface. In addition, our iterative process of multi-sensor data fusion and registration is guaranteed to converge to a minimum error.

3. Mathematical formulation for surface-based data fusion, and data withdrawal and data registration

The mathematical formulations for surface-based data fusion, data withdrawal and data registration are the key to our IRF method and are described in this section. They include: (1) B-spline surface representation, (2) Kalman filter based data fusion, (3) data withdrawal, and (4) data registration. Although Kalman filter-based surface fusion has been introduced in [14,17,38,39], Kalman filter-based data withdrawal is novel and is used in our IRF process.

3.1. B-spline surface representation

In the IRF method, the underlying surface for data fusion and registration can be of planar, cylindrical or free-form B-spline surfaces. Without loss of generality, we use the B-spline as the basic surface representation for our introduction of the IRF method since the B-spline surface can represent free-form surfaces and has been widely used in product design and manufacturing. A brief discussion on other types of surfaces is also provided in Section 3.5.

A bi-cubic B-spline surface has the form:

$$S(u, v) = \sum_{i=1}^{n_u} \sum_{j=1}^{n_v} B_i(u) B_j(v) \mathbf{P}_{ij}, \tag{1}$$

where B is the B-spline shape function and $\mathbf{P}_{ij}$ is the ij-th control point (number of control points is $n = n_u \times n_v$). The equation can also be expressed in a matrix form:

$$S(u, v) = \mathbf{A} \cdot \mathbf{P}, \tag{2}$$

where $\mathbf{A}$ is the B-spline shape function vector (of dimension n), and $\mathbf{P}$ represents the collection of control points (of dimension n). See [23] for details on the B-spline surface representation.

3.2. Data fusion

In order to fuse multi-sensor data which has different sensor noise (we assume that the noise is independent, white and Gaussian) into a B-spline surface, we choose the Kalman filter (a recursive least-squares method) [40] to produce the optimal estimate of the surface in a least-squares sense.

Given a sensor measurement z on the surface $S(u, v)$ with parameters (u_z, v_z), Eq. (2) tells us its position is

$$z = \mathbf{A}_z \cdot \mathbf{P} + \varepsilon, \tag{3}$$

where $\mathbf{A}_z$ is the B-spline shape function matrix, and ε is the measurement of noise.

In the terminology of the Kalman filter, the above B-spline surface equation represents a linear system between the internal surface state and external observations z [38,39]. That is, the collection of control points $\mathbf{P}$ constitutes the internal state of the object shape, the measurement z with its covariance forms the external observations of the B-spline surface, and $\mathbf{A}_z$ corresponds to the measurement matrix. Then the Kalman gain [14]:

$$\mathbf{K}_l = \mathbf{\Lambda}_{\mathbf{P}_{l-1}} \mathbf{A}_z^{\mathrm{T}} \left(\mathbf{A}_z \mathbf{\Lambda}_{\mathbf{P}_{l-1}} \mathbf{A}_z^{\mathrm{T}} + \Lambda_z \right)^{-1}, \tag{4}$$

where $\mathbf{K}_l$ is the l-th step Kalman gain, $\mathbf{\Lambda}_{\mathbf{P}_{l-1}}$ is the covariance of state $\mathbf{P}_{l-1}$ at the $(l-1)$-th step, and $\mathbf{\Lambda}_z$ is the variance of measurement z.

The surface state and covariance updating equation is:

$$\mathbf{P}_l = \mathbf{P}_{l-1} + \mathbf{K}_l \left(z - \mathbf{A}(u_z, v_z) \mathbf{P}_{l-1} \right), \tag{5}$$

$$\text{and (a)}: \mathbf{\Lambda}_{\mathbf{P}_l} = \left(\mathbf{I} - \mathbf{K}_l \mathbf{A}(u_z, v_z) \right) \mathbf{\Lambda}_{\mathbf{P}_{l-1}}$$

$$\text{or (b)} \; \left(\mathbf{\Lambda}_{\mathbf{P}_l} \right)^{-1} = \left(\mathbf{\Lambda}_{\mathbf{P}_{l-1}} \right)^{-1} + \mathbf{A}^{\mathrm{T}} (u_z, v_z) \left(\Lambda_z \right)^{-1} \mathbf{A} (u_z, v_z). \tag{6}$$