An iterative framework for registration with reconstruction

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Abstract

The core of most registration algorithms aligns scan data by pairs, minimizing their relative distance. This local optimization must generally pass through a validation procedure to ensure the global coherence of the resulting alignments. This work introduces an iterative framework to guarantee the global coherence of the registration process. The iteration alternates registration and reconstruction steps, including alignments with the proper reconstructed surface, until the alignment of all the scans converges. The framework adapts to different contexts by choosing which scans are aligned and which are used for the reconstruction. This choice is based on the alignment and reconstruction errors. Derivations of this framework are presented with a rough automatic registration, increasing its robustness.

1 Introduction

Three-dimensional scanning builds virtual models from several views of the same real object. Each view or *scan* generates a range image, i.e. a set of points in 3D with its own coordinate system. The registration process defines an optimal common coordinate system for all the scans, which is a necessary pre-processing of shape reconstruction algorithms. This optimal alignment is usually determined by minimizing over all the rigid transformations a distance between the overlapping parts of the scans. The basic optimization algorithm is the Iterative Closest Point (ICP) [1, 2], which aligns each pair of scans separately. Since the scans are views of a unique rigid object, a global optimal alignment must exist. However, the scanning process is prone to noise [15], and the local minima must then be checked for global consistency.

In this work, we propose to use and schedule intermediate reconstructed models to improve the registration process, extending the early work of Jin *et al.* [24]. This reconstruction step provides a feedback on the current alignment quality and on how to correct it for the final reconstruction: We align a selected subset of the scans with the reconstruction, generating a new alignment that is used for a subsequent reconstruction. The reconstruction generates

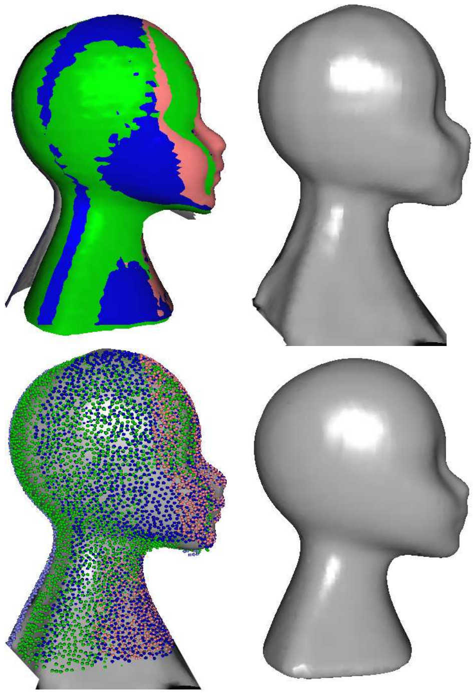
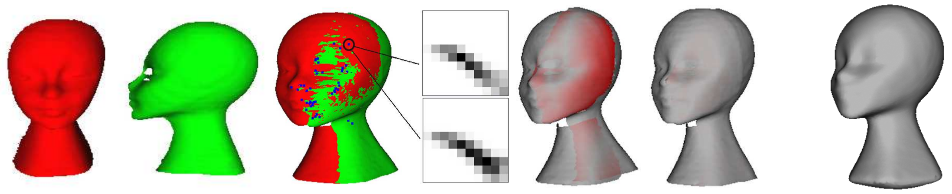


Figure 1: Correcting alignment with the reconstruction: The rough, pair-wise positioning accumulates errors (top left), which leads to false features at scan boundaries in the reconstruction (top right). Re-aligning with this reconstruction ensures the global coherence (bottom left), significantly improving the final reconstruction (bottom right).



(a) A pair of scans. (b) Spin-Images of corresponding points on the two scans. (c) Fine alignment with ICP. (d) Reconstructed model.

Figure 2: The basic elements of a reconstruction pipeline: from the several scan data in their own coordinate systems (a), a local geometry descriptor is used to derive a rough position (b). This alignment is refined by distance minimization (c). The registered scans are finally merged into a single surface (d). The color in (c) codes the maximal distance between two scans in the view direction.

an updated model to align with, repeating the process until this virtuous loop converges (Figure 1). The alternation of alignment and reconstruction on different selection of scans adapts the general registration process to different contexts, such as dynamic or multi-resolution registration. In particular, it can improve the registration precision (basic framework), achieve delicate registration (overlapping maximization), improve the registration robustness (divergence correction), decrease the total execution time (multi-resolution) or further integrate the whole scanning/reconstruction process (dynamic registration).

Related works. Usual automatic registration involves two steps: initial positioning and refinements of this alignment with global coherence validation.

The registration process searches for rigid transformations, which are low-dimensional solutions (6 dimensions per scan), from high dimensional data (3 dimensions per scan point). Using global optimization [17, 21] or statistical analysis [19, 18], one can directly align all the scans simultaneously. The problem can also be considered partially by aligning the scans pair-wise. To avoid working with all the points of a scan at once, several techniques use local descriptors that are invariant under rigid motions. In this work, we use spin images [11] as a shape descriptor, similarly to previous works [22, 4]. Robust descriptors can also be combined with the point selection [5]. Further references on this initial positioning can be found in [3].

This positioning is generally refined by local minimization algorithms, such as the classical Iterated Closest Point (ICP) algorithm [1, 2]. This algorithm has been improved in speed [23], accuracy and robustness [12, 9, 6]. Further references on the ICP variations can be found in [14].

In order to avoid local minima of the ICP, the current alignment is checked for consistency. This consistency usually comes either from a global optimization [21] or from a dependency graph of the pair-wise alignments [17, 25, 22]. In this work, we propose to use and schedule reconstructions steps in the registration pipeline to guarantee this global consistency.

The introduction of reconstruction in the registration process was first described in [24], which used the pioneering reconstruction method of [8]. They reconstruct the surface from all the aligned scans during the registration, and align all the scans with the reconstructed surface. Further constraints can be added by aligning the scans with a pre-defined model [10]. We propose here a generalization of these ideas by scheduling which scan is aligned or reconstructed at each step. Among the many surface reconstruction methods, we test our framework with two of them: the Multiple Partition of Unity implicits of [20], and the Poisson inversion of [13].

Contributions. This work introduces a general framework for the use of reconstruction inside the registration pipeline. This reconstruction provides a global feedback on the quality of the alignment. Since the reconstructed surface is generally a mesh which approximates the scan, the original scans can be aligned with it using robust algorithms such as ICP derivatives. This leads to a globally coherent registration without global optimization or consistency graph. Moreover, the final registration is automatically optimized for the reconstruction, avoiding false feature at misaligned regions [15].

Figure 3: Improvement of the global alignment using the reconstructed surface: misaligned scan data (left) is realigned with the reconstruction to improve the final alignment (right).

We incorporate this reconstruction step to a framework built on three basic steps: 1) initial positioning, 2) local refinement of an alignment and 3) reconstruction (Section 2). By scheduling these steps and choosing on which scans they are applied, we open this registration framework to different contexts such as dynamic or multi-resolution registration (Section 3). We implement this framework with simple algorithms for each step (Section 4), significantly improving the global robustness of the registration (Section 5).

2 Framework Elementary Steps

In this section, we recall basic examples of scan descriptors for the initial positioning, alignment refinement and surface reconstruction (Figure 2). These elements are representative of the three elementary steps of our registration framework.

Spin Image Descriptor. Spin-Images [11] describe the surface shape in a short range around a reference point (Figure 2(b)). Given a reference point on the surface, the near-by surface points are projected on its tangent plane, and encoded in a bi-dimensional radial coordinate system that is invariant to rigid transformations. The spin image at the given point is the gray-scale image representing the density of points in this coordinate system. From the invariance of the system, corresponding points in different meshes generate similar spin-images even with clutter and occlusions.

Iterative Closest Point. The Iterative Closest Point (ICP) algorithm [1, 2] iteratively refines an initial alignment of two meshes (Figure 2(c)). It converges to a local minimum that can be the expected rigid transformation, depending on the initial condition. According to [14], the original algorithm and its many variations are composed of six stages: scan points' selection, matching, correspondences generation and filtering, error metric definition and minimization over the rigid transformation. The rigid transformation that minimizes the error is then applied to the scan points and the process is repeated until the rigid transformation is close enough to the identity.

Surface Reconstruction. Surface reconstruction consists in defining a continuous surface representation from a set of isolated points in space [8] (Figure 2(d)). Registration techniques are often used as a pre-processing step for reconstruction [16]. In this work, surface reconstruction serves as a global check for the registration. We illustrate this concept with one global-from-local and one global reconstruction algorithms: the Multiple Partition of Unity (MPU) [20] and the Poisson surface reconstruction [13]. The first one fits a tri-variate polynomial on the scan points contained in each leaf of an adapted octree, and blends these implicit representations by means of radial functions centered at the near-by leaves. The second one builds the characteristic function of the volume inside the surface. To do so, it solves a global linear system whose equations match the pseudo-derivatives of this characteristic function to the normal at each scan point, generating one linear equation for each derivative kernel at the center of an adapted octree.

Error Measures. In order to schedule in our framework which scans are aligned and which are reconstructed, some error measures are derived from each step of the pipeline. The initial positioning error is measured by the geometric consistency of spin image correspondences, i.e. the difference of the distances between the correspondences on each scan. The ICP error, i.e. average of distances between correspondences measures, is used to estimate the alignments accuracy. The reconstruction error is estimated directly from the reconstruction algorithm: the fitting error in each leaf for the MPU case, or the linear solver error in the Poisson case.

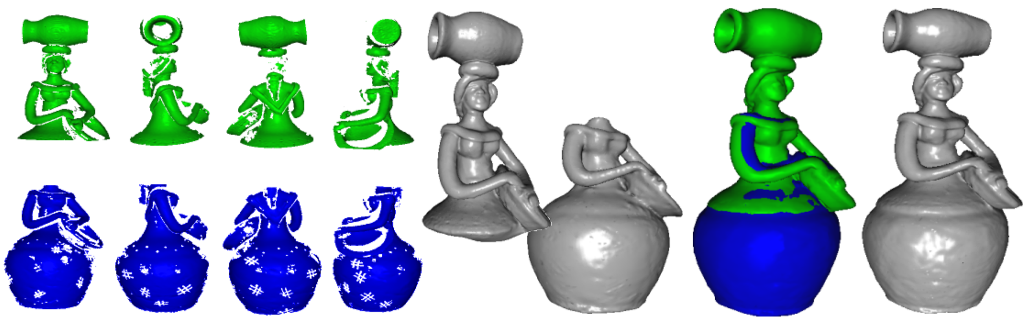


Figure 4: Derivation of our framework for overlapping maximization on a complex model, whose upper and lower parts are acquired in two separate sessions. Registering the models reconstructed separately from the upper and lower parts increases the overlapping parts, improving the stability of the alignment.

3 Registration with Reconstruction Framework

The usual registration pipeline starts with a rough positioning of the scans, which are then aligned by minimizing a distance between them. The aligned scan is then piped into a reconstruction algorithm to produce the final surface. We propose here a general framework to improve the alignment using the reconstructed surface, introducing a feedback in the registration process (Figure 3). This reconstructed surface serves a triple purpose. First, it allows measuring the quality of the registration of each single scan by computing its distance to the reconstructed surface. Second, aligning a scan with the reconstruction improves the registration and optimizes it for reconstruction. Third, this re-alignment guarantees a global coherence of the registration without global optimization, avoiding fake features due to misalignment.

Basic framework. Our framework is built on top of three basic steps:

1. Rough positioning of two distant meshes.
2. Fine alignment of two almost aligned meshes.
3. Reconstruction from several aligned meshes.

The reconstruction step serves to check and improve the alignments in different manners, depending when and how it is scheduled within the framework. For example, the iterative refinement of [24] consists in alternating the two last steps with all the scans at once, aligning them with the last reconstructed mesh.

Note that in steps 1 and 2, one of the meshes to be aligned can be the (partially) reconstructed surface itself. This is the key to transform the local problem into a global one. Furthermore, depending on the scheduling, i.e., which meshes are aligned and reconstructed at each stage, this framework adapts registration to different usages. We comment hereafter derivations of our framework in four different registration contexts: overlapping maximization, dynamic registration, divergence correction and multi-resolution.

Overlapping maximization. Complex objects are generally scanned in several sessions, typically obtained by rotating the objects in front of the scanner (Figure 4). While the overlapping between two consecutive scans of the same session is likely to be high, the overlapping between the scans of two different sessions may be too small to find a stable optimal alignment. Moreover, the rotation angle used inside a session provides a good relative initial positioning of the scans, while the alignment between sessions is not given *a priori*. For example on Figure 4, the upper and lower parts of the object overlap on a very small horizontal band. However, the overlapping of all the scans of one session with all the scans of another session is necessarily more extended. By reconstructing the aligned scan of each session and aligning only the reconstructed meshes, we benefit from this bigger overlapping.

More generally, we can choose at each step to reconstruct with all or only part of the scans, and align pairs of scans, mixed pairs of scan/reconstructed mesh, or only reconstructed meshes. This choice

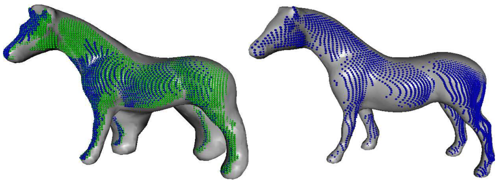


Figure 5: Derivation of our framework for dynamic registration. Partial reconstructions help the alignment, producing a complete reconstruction from only 5 of the 7 scans. (Left) Reconstruction from 2 scans with the Poisson method already generates the two rear legs. (Right) The 6^{th} scan aligned with the reconstruction from 5 scans.

may depend on the available processing time and on the error of each pair-wise ICP, such as the one described at Section 2.

Dynamic registration. When registering on-the-fly during the scanning process, or when computing the initial alignment incrementally, the scan added last must be aligned with all the previous ones (Figure 5). This process can be costly and unstable, in particular if this last scan overlaps with only a few of the previous ones. Since the reconstructed mesh should contain the details of each scan, aligning the new scan with it maximizes the overlapping area, reducing the number of incorrect correspondences. We can thus derive our framework to align the scan added last with the reconstruction of the previous one. The reconstruction can be performed after each scan addition, or when the error between the scans added last and the current reconstruction is bigger than a threshold, which means the aligned scans and the reconstruction are geometrically inconsistent. To improve the stability, the initial scans can be periodically re-aligned with the reconstruction.

Moreover, the registration of the previous scans can be improved by regularly scheduled steps of pair-wise alignments. This strategy is best used in real-time data acquisition for 3D reconstruction.

Divergence correction. Our general framework is an iterative process that converges depending on the initial alignment. When starting from a bad positioning, the process may oscillate between wrong alignments. This can be easily checked by tracking the transformations applied to a specific scan at each stage and the final error after a fixed number of ICP iterations (Figure 8). If these transformations remain far from the identity or if the error does not diminish, the scan can be re-aligned from scratch, using the rough positioning with the mesh reconstructed from all but this scan.

The convergence of our general framework can be improved by alternating global and local alignments: aligning all the scans with the reconstructed mesh (global) and aligning pairs of scans in sequence (local). Each alignment procedure returns an error (cf Section 2), which can be used to correct eventual divergent behaviors.

Multi-resolution. The resolution of the reconstructed mesh can be adjusted, either directly in the reconstruction algorithm tuning or explicitly by mesh simplification and refinement operations. Aligning a low-resolution reconstructed mesh with decimated scans produces a quick and coarse registration. Increasing the resolutions then incrementally improves the alignments. (Figure 6). This coarse-to-fine registration fills the gap between the rough positioning of distant meshes and the ICP alignment, reducing considerably the execution time. Moreover, this strategy improves the robustness of the registration on very noisy objects, avoiding local noise to be considered as features. This way, we obtain good results with only 2 or 3 different resolutions. For example, using two resolutions of 900 and 7000 points for each of the 6 scans, the total execution time for registration of the low resolution, reconstruction of the high one and aligning with the reconstructed surface is 47 seconds, while the conventional registration procedure lasts 256 seconds.

4 Implementation

The overall implementation of our framework is simple provided the basic elements described in Section 2, since meshes are the natural representation of both the original scans and the reconstructed surfaces. We implement the basic steps of the framework by using an automatic pair-wise alignment method for the first step, point-to-point ICP for the second step. For the third step, we use the available implementations of the MPU and Poisson reconstructions *as is*.

Model	# views	# points $\times 10^3$	Frame- -work	Posit- -ioning secs.	Recons- -truction	secs.	ICP secs	# iter.	Error $\times 10^{-4}$
bunny	12	13	corrective	14	MPU	1.6	8.1	9	2.0
head	5	16	basic	41	MPU	1.8	7.2	9	1.8
hand	6	21	mutlires	7.0	MPU	3.5	3.1	2	9.2
horse	7	22	dynamic	4.6	Poi	3.3	4.8	2	3.2
lady bot	8	54	overlap	322	Poi	125	0	0	2.0
lady top	12	174	overlap	660	Poi	1340	75	2	1.5
lady	2	228	overlap	72.5	Poi	2486	0	0	2.0

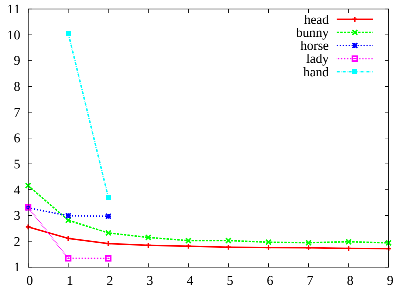


Figure 7: Some experiments on real objects (head, lady) and virtual models (horse, bunny, hand). The graph maps the maximal error from the number of iterations. The timings are averages per iteration, where one iteration corresponds to an alignment and a reconstruction step in the different frameworks. The error corresponds to the maximal ICP error of the last step.

The initial alignment of the first step can be either manual, deduced from the calibrated scanner position, or automatic. For this last case, we use an automatic alignment strategy similar to [22, 9]. Using the terminology of [3], it consists in selecting feature points based on their curvature in each scan, representing them by spin images and ranking matching images by the difference of their pixels. Groups of matching are valid if the distance between them inside each scan is similar. Valid groups can be discarded if they induce a too small overlap. In our experiments, the bin size of the spin-images took values between 2 and 4, and the spin-image width between 10 and 15.

The ICP variant used can be described in the terminology of [14] by: all points selection, matching based on Euclidean closest point using kd-trees, filtering sets of correspondences according to a distance threshold, squared error metric and minimization using quaternions following [7]. Finally, to emphasize the generality of our framework, we use two different reconstruction techniques, respectively [20, 13].

5 Experiments

We consider two sets of examples: artificially generated scans such as the *horse* model (Figure 5), where the correct alignment is the identity, and scanned objects such as the *head* and the *lady* (Figures 1, 2 and 4) to test the robustness to real scanner noise. We forced extreme cases with wrong initial alignments on an artificial scan of the *bunny* (Figure 8), or with flat overlapping area on the low resolution *hand* model (Figure 6).

Precision. In the different frameworks proposed, we obtain a significant improvement compared to a single alignment/reconstruction step involving all the scans. Detailed results on the illustrations of this work are reported on Figure 7. Observe that, for small or decimated models, the several reconstruction steps count only for a fraction of the total time, while it gets a higher proportion on bigger models. Even with initial alignment far from the correct position (Figure 8) the registration converges in a few iterations. Except for the extreme case in Figure 5, results obtained using MPU and Poisson reconstructions are similar.

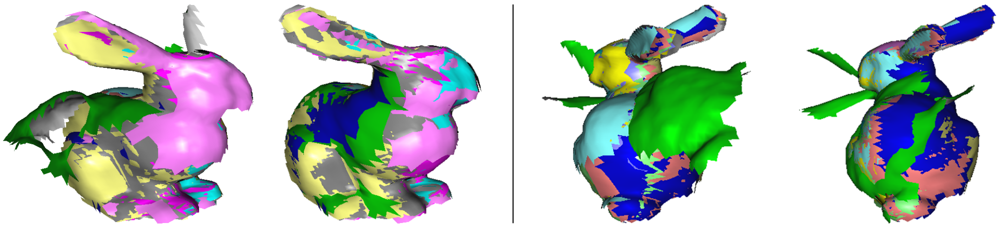


Figure 8: Derivation of our framework for divergence correction. This method improves the robustness of the global registration, and minimizes the impact of bad initial alignments: The error induced by artificially rotating one scan by 60 degrees is progressively corrected in 3 reconstruction/alignment iterations (left). Without the divergence correction, the ICP fits the scan to another position due to its symmetry (right).

Limitations. The proposed framework is very efficient in term of precision and adaptation to diverse contexts. However, since we did not optimize the reconstruction and alignment steps for consecutive calls, the overhead in execution time is still significant on big models without the multiresolution strategy. The resolution settings of the reconstruction have an impact on this execution time, and also on the quality of the alignment, in particular since we use point-to-point ICP. Except for the multiresolution of Figure 6, we let the resolution of all the reconstructions to their default parameters.

6 Conclusions

In this work, we propose a novel framework for registration, inserting and scheduling a reconstruction step to improve the final alignment of the scans. Variations of this scheduling adapt this framework to different contexts. These reconstruction steps provide a feedback to intermediate alignments and guarantees the global coherence of the alignment. They further optimize the alignment for the final reconstruction, avoiding fake features at the frontier of misaligned scans. This framework extends the work of Jin *et al.* [24], adapting global registration to different contexts. Moreover, it gives a simple way for registration to benefit from the recent advances in surface reconstruction.

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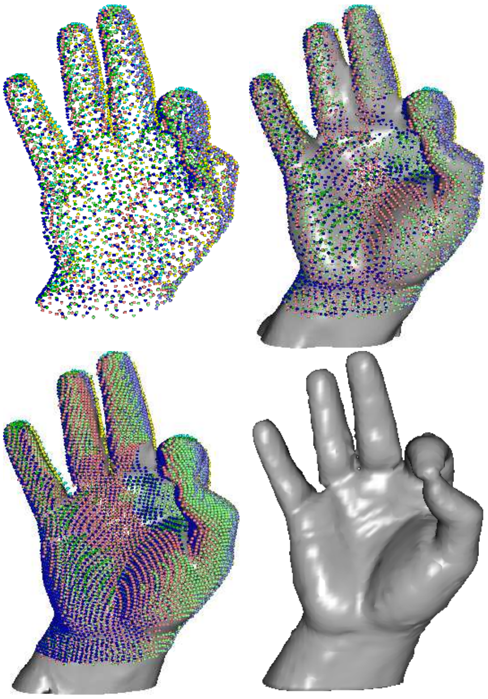

Figure 6: Derivation of our framework for multiresolution registration: aligning decimated scans generates a quick and rough initial positioning (top left), which is reconstructed (top right) and refined by increasing the resolutions of both the scans and the reconstructed surface (bottom). In this example, this process was five times faster than a direct registration.

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