Abstract—In many applications, maintaining a consistent dense map of the environment is key to enabling robotic platforms to perform higher level decision making. Several works have addressed the challenge of creating precise dense 3D maps. However, during operation over longer missions, reconstructions can easily become inconsistent due to accumulated camera tracking error and delayed loop closure. Without explicitly addressing the problem of map consistency, recovery from such distortions tends to be difficult. We present a novel system for dense 3D mapping which addresses the challenge of building consistent maps while dealing with scalability. Central to our approach is the representation of the environment as a manifold map, comprised of overlapping Truncated Signed Distance Field (TSDF) volumes. These volumes are localized through feature-based bundle adjustment. Our main contribution is to use a probabilistic measure to identify stable regions in the map, and fuse the contributing subvolumes. This approach allows us to reduce map growth while still maintaining consistency. We demonstrate the proposed system on publicly available datasets, as well as on a number of our own datasets, and demonstrate the efficacy of the proposed approach for building consistent and scalable maps.

I. INTRODUCTION

Vision-based perception systems are increasingly being deployed for use on robotic platforms that operate in unstructured environments, or without access to reliable GPS coverage [1]. In addition to offering a sensing solution that does not depend on any external infrastructure, the benefits of such systems include their low weight, low cost and the richness of the data they provide.

Key competencies towards achieving high level tasks for robotic systems utilizing vision, are building an internal representation of the environment, and localizing within it. This problem, the Simultaneous Localization And Mapping (SLAM) problem, has been a focus of robotics research for the last three decades. Most successful SLAM systems utilizing visual data simplify the problem by converting incoming images to a set of visual features, before estimating the camera motion and the map as a function of only these feature observations [2]. A summary of past and present SLAM systems can be found in [3].

While feature-based systems have proven themselves effective for camera localization, a map comprised of a sparse collection of 3D points is typically insufficient for further tasks. As such, many robotic systems build dense 3D maps of their environment, often in parallel to sparse maps [1]. Recently, the commodification of depth cameras has seen impressive results produced in the field of 3D reconstruction from visual sensors [4], [5]. The techniques used by these works are now making their way into robotics applications [6], [7]. However, the shortcomings of SLAM systems is that they suffer from imperfect odometry, accumulated pose drift, and delayed loop closures. These can produce inconsistent reconstructions if these effects are not handled explicitly, see Fig. 1.

This paper introduces a novel mapping system which addresses the challenge of maintaining map consistency and scalability. Central to our system is the representation of the observed scene as a manifold map, first introduced in [8]. The manifold consists of overlapping TSDF subvolumes. In our approach we create new subvolumes early and often to limit the amount of intra-volume distortion. To limit the resulting map growth we perform subvolume fusion where doing so is very likely to produce consistent results. We first follow a landmark covisibility [9] based approach to identify subvolumes containing potentially redundant views of the environment. In a

Figure 1: Reconstruction of one floor of an office building viewed from the top. The path taken by the agent includes frequent place revisiting. However, due to viewpoint differences loop closures are significantly delayed. The reconstruction produced by a global TSDF map (a) contains significant inconsistencies, while our manifold based system (b) is able to correct for these distortions.

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The main contributions of our system are,

- a dense map maintained as a manifold comprised of overlapping TSDF volumes;
- probabilistic system for maintaining consistency while limiting the growth of the map;
- completely CPU-based to allow for use on lightweight robotic platforms which usually lack GPU hardware.

II. Related Work

There has been extensive work on SLAM over the last three decades, of which visual SLAM forms a significant part [3]. Dense 3D mapping from image data has also received considerable research focus and in recent years there has been a surge in the number of works in this field. A plethora of systems have been developed, for which we give a brief review of the most relevant.

Dense mapping systems have employed a number of different representations of the environment, a choice which determines many properties of the resulting system. Engel et. al. [10] represent the world as a collection of well localized depth frames produced by multi-view stereo. Keller et. al. [11] represent the world as a collection of surfels in 3D space. Another approach is occupancy grids which represent the world as a collection of occupancy probabilities stored over a voxel grid [12] and have been applied successfully to robotic systems in the past [1]. In this work we represent the observed world by maintaining a TSDF over a discrete grid, an approach which has shown compelling results in recent years [4]. Such representations offer a systematic method for incremental fusion of noisy depth frames, provide high fidelity reconstructions, and make no assumptions about the structure of the environment. Recent works on sparse representations of TSDFs have shown that these techniques can also be employed at larger scales [13]. Furthermore, keyframe-depth maps or surfels produce accurate reconstructions, however these representation are likely to be challenging to use directly for robotic tasks such as motion planning. The TSDF based volumetric representation of the world is more conducive for such tasks, where free space and surface connectivity information are important [7], [6].

Most existing TSDF-based reconstruction systems use frame-to-frame or frame-to-model alignment for tracking the sensor pose at each frame, before integrating depth data into the map [4] [13]. Incremental systems such as these inherently suffer from camera tracking drift, which can lead to dramatic distortions in the reconstructed environment [13]. There have been several works which aim to address the challenge of producing consistent dense maps, of which we review the most relevant.

Whelan et. al. [5] introduce a system which restricts the volume of active TSDF reconstruction, converting data leaving this area to a triangular mesh. Then, rigid-as-possible deformations of the global mesh are used to maintain consistency. ElasticFusion [14] took a similar approach to maintaining consistency, achieved by bending a surfel-based map, which allowed for place revisiting [5]. BundleFusion [15] enforced consistency by storing the history of integrated frames. Camera poses are then globally optimized with each arriving frame and the reconstruction updated, producing compelling globally consistent reconstructions. This method however would likely face scalability issues during on-line use.

Another approach to maintaining map consistency is to represent the global map as a combination of TSDF subvolumes. The global reconstruction is then recomputed as a function of these subvolumes only. Several works have shown the efficacy of such an approach [16], [17], [18], [7], [19]. These works can be broadly separated into two categories; those that attempt to partition space to minimize subvolume overlap, and those that do not partition space.

Partitioning the workspace means that the constructed map size grows linearly with the size of the observed environment, rather than time or trajectory length. Patch Volumes [15] divides the observed scene into “map patches”, which are aligned with planar surfaces in the environment. In a similar approach Kühler et al. [12] attempt to minimize subvolume overlap. While space efficient, there are two disadvantages of pursuing an approach of subdivision. Firstly, when revisiting an existing subvolume, one must ensure the camera pose is consistent with that volume in order to integrate the information, which in practice is difficult. Secondly, both [16] and [17] require ray casting into several subvolumes simultaneously to perform camera tracking. Such an approach requires GPU-based processing, which at present is likely to limit the applicability of such systems to lightweight robotic platforms.

By contrast, several systems [18], [7], [19] make no attempt to partition space or to control subvolume overlap. The authors in [18] build reconstructions as a composition of mesh fragments and produce compelling results. Both systems however, are aimed at producing high quality reconstructions in post processing, leading to high computation times, making these approaches inappropriate for robotics applications. The authors in [7] and [19] represent the observed world as a number of potentially overlapping TSDF volumes and show this to be effective for maintaining map consistency. We continue the development of this approach. The main drawback of existing works in this direction is that the maps they produce grow linearly either with the trajectory length [7], or with time [19]. Our proposed approach differs from these systems in a number of technical aspects (see Section IV), however the main scientific novelty of our system is to address the scalability problem by introducing a systematic approach to limiting map growth.

To summarize, the existing approaches which address the challenge of maintaining consistency in dense maps either: a) maintain a map in a form which requires further processing, for example point clouds or keyframe depth maps; b) make revisiting previously mapped locations difficult; c) use offline or
computationally expensive techniques for global optimization of the reconstruction; d) build maps which grow in size without bound, even in a bounded size environment. We propose a system to address consistency and scalability issues together.

III. Problem Statement

Given a sequence of images $\{I^i\}_{i=1}^M$, associated depth maps $\{D^i\}_{i=1}^M$, and camera coordinate frames $\{C^i\}_{i=1}^M$, we aim to build a dense 3D map of an observed scene. The camera coordinate frame $C^i$ is parameterized as a rigid transformation with respect to a global reference frame $G$ as $T^{GC^i} \in \text{SE}(3)$. Central to our approach is the use of a TSDF for implicit surface representation [4], which we denote as $F$. Within some truncation band around an observed surface, the function $F: \mathbb{R}^3 \rightarrow (d, w, c)$ maps 3D points to a tuple, consisting of $d$ the distance to the nearest observed surface, $w$ a weighting/confidence measure, and $c$ the observed color. Outside of this truncation band the function is not defined.

As is common in recent reconstruction systems [13], [20], we store this function as a collection of sparse samples over a discrete uniformly-spaced voxel grid.

If the set of poses $\{T^{GC^i}\}_{i=1}^M$ is well determined at the time of image capture, existing techniques [4], [13], [20] can be used to construct a global TSDF map. We however, focus on the case where camera frames are not well globally localized at the time of capture, for example due to accumulated drift or delayed loop closure.

IV. System Description

The proposed system builds on the TSDF mapping techniques first presented in [4] and later expanded by a number of works [20], [5], [13]. An overview of our system is shown in Fig. 2 and consists of modules for camera tracking/localization (Section IV-B), volumetric integration (Section IV-C), map maintenance (Section IV-D), and map fusion (Section IV-E). We start with a description of manifold representations for mapping.

A. Manifold Mapping

When represented as a manifold, a map is embedded in a space of higher dimensionality than the environment it represents [8]. The motivation for pursuing this representation here is that when fusing observation data into a global (non-manoifold) map, inconsistencies can be caused by integrating data when camera localization is imperfect. Particularly in the case of dense maps, such errors tend to be difficult to recover from because, in contrast to sparse maps, the correlations between environment observations and localization information tend to be lost in order to ensure mapping remains efficient. By contrast, a manifold map remains consistent by construction. In a robotics context this is particularly relevant as such a system allows for place revisiting, while guaranteeing that the map is not corrupted, even when place recognition is arbitrarily delayed.

A manifold is a continuous construct, however, in a practical system it is typically represented by a discrete approximation [8]. Our manifold consists of a number of overlapping TSDF volumes, called patches following [8] and [16]. Each patch represents a small section of the manifold. The total map is then represented by the collection of all such patches, such that

$$\Pi = \{\pi^p\}_{p=1}^N$$

where $N$ is the number of currently constructed patches. Each patch $\pi^p$ has a local coordinate system $M^p$ associated with it, parameterized by $T^{GMP} \in \text{SE}(3)$.

While storing a collection of subvolumes shares some similarities to a sub-mapping approach, there is a clear difference; sub-mapping typically attempts to partition space, maintaining a one-to-one relationship between the world and the map. In contrast, representing the world as a manifold allows for a one-to-many relationship. While somewhat unintuitive, this approach is advantageous for maintaining consistency. Multiple (potentially conflicting) views of the environment are able to remain separate in the manifold, until the conflicts can be disambiguated, which can be arbitrarily delayed.
B. Camera Localization

We utilize sparse, feature-based SLAM for providing the current sensor pose, as well as updates to past poses. Typical TSDF systems have tended to rely on dense (depth) image alignment for camera tracking. The relative merits of these approaches with respect to sparse systems is an ongoing debate, however, in the context of this work the use of a sparse system offers two advantages: 1) modern sparse localization systems run efficiently on a CPU allowing application to lightweight robotic platforms, and 2) a sparse feature map, in which correlations between localization information and the environment are maintained, allows probability-based decision making, as discussed in Section [V-D].

For this work we make use of a modified version of ORB-SLAM2, which has shown state of the art performance on public datasets [2]. However, the novelties of this work are not tied to any particular SLAM system. The use of bundle adjustment is central to our system and we therefore state briefly the main properties of the bundle adjustment factor standard in modern visual slam, ORB-SLAM2 maintains all the location of mapping fidelity in the particular thread. Upon loop closure the extent of these subsets determines the level of probability-based decision making, as discussed in Section [IV-D].

D. Map Maintenance

In this section we discuss how we handle loop closures to maintain map consistency while also limiting growth of the map. Following a loop closure, camera tracking provides an updated set of keyframe poses resulting from global optimization of the sparse map. The representation of the environment within each patch, as relative to a patch base frame, makes updating the dense map easier; patch coordinate frames \( \{M^p\}_{p=1}^N \) are simply updated with their associated keyframe poses from the sparse map.

The system described thus far will produce a manifold which increases in size linearly with trajectory length, meaning that even during operation in bounded size environments, the map grows without bound. This characteristic would limit the practical applicability of such a system. When revisiting a place, the manifold is likely to contain multiple potentially redundant views of the same area. Our approach to limiting map growth is to identify these redundant views and fuse them, where doing so would produce consistent results. We utilize the information contained in the sparse feature map to assist us in this process.

To identify patches which contain redundant views, we utilize a modified version of the covisibility graph [9]. During construction of the manifold we associate each keyframe \( K^i \) with the patch to which it contributed. We then build a weighted graph \( G = (V, E) \) where the vertex set \( V \) represents the \( \pi^i \) landmark locations \( \{\pi^i\}_{i=1}^N \), and the edge set \( E \), with associated weights \( W \), represent landmark covisibility information. Formally, vertex \( i \) and \( j \) have an edge of weight

\[
W_{ij} = |L_i \cap L_j|,
\]

where \( L_i \) and \( L_j \) are the sets landmarks observed by keyframes contributing to patches \( \pi_i \) and \( \pi_j \), and here \( |\cdot| \) indicates the cardinality of the set. Patches connected with an edge of high weight in this graph are likely to have viewed the same area, and therefore are passed as candidates for fusion to the next stage.

At this stage we have a list of patch pairs which contain views of similar sections of the environment. However, the estimated pose of the coordinate frames associated with these patches

\[
T_{MACi} = (T_{GM}A)^{-1} \otimes T_{GCi},
\]
may contain significant localization errors. Fusing such pairs is likely to produce inconsistent results, and we would therefore rather maintain these views separately (as they currently exist) in the manifold. Thus, before fusing patch pairs we determine a measure of the accuracy of their relative localization. Formally, given a patch candidate pair $(\pi_i, \pi_j)$, with base-frames $M_i$ and $M_j$, and associated with keyframes $K_i$ and $K_j$, we define $q(i,j)$ the quality measure of their relative localization as

$$q(i,j) = 1/\| \Sigma_{i|j} \| , \quad (7)$$

where $\Sigma_{i|j}$ is the covariance matrix associated with the conditional distribution $P(K_i|K_j)$. For this work the norm $\| \cdot \|$ is the 2-norm, which is proportional to the volume of an ellipsoid of constant probability density defined by $\Sigma_{i|j}$. Patches meeting a minimum value of $q$ are fused into a single patch. In the remainder of this section we discuss how $\Sigma_{i|j}$ is determined.

1) Extraction of the Patch Conditional Covariance: Given an initial guess of the optimization parameters $\theta = (K, \lambda)$, solving bundle adjustment proceeds by iteratively linearizing the graph and solving the a linear system,

$$H\theta = b, \quad (8)$$

where the typically sparse matrix $H$ and vector $b$ are determined from the measurements, their Jacobians, covariances, and linearization point (see [21] for a detailed exposition). At convergence we are left with an approximation of the information matrix

$$I \equiv H^* , \quad (9)$$

where $H^*$ results from linearizing the graph at the convergence point $\theta^*$. Inverting the information matrix $I$ to get $\Sigma$ is extremely computational expensive and does not scale to practical problems. However, determining $\Sigma_{i|j}$ for each patch-pair only requires very few blocks of the full matrix $\Sigma$; two diagonal blocks and a single off diagonal block. We aim to extract only these blocks, and proceed as follows. We first marginalize out the landmarks from the graph by forming the Schur complement of the matrix $I$, leading to

$$I_P = H_{pp} - H_{pl}H_{ll}H_{lp}^T \quad (10)$$

where we order keyframes and landmarks such that

$$H = \begin{bmatrix} H_{pp} & H_{pl} \\ H_{lp}^T & H_{ll} \end{bmatrix} \quad (11)$$

The matrix $I_P$ is the information matrix associated with the graph following landmark marginalization. Due to the diagonal structure of $H_{pp}$ and $H_{ll}$, and the sparsity of $H_{pl}$, this reduction can be performed very efficiently (see [21] for further details).

From here we employ a modified version of the dynamic programming approach based on Cholesky decomposition of the information matrix introduced in [23]. In brief, given a requested element of the covariance matrix $\sigma_{i,j}$, the algorithm progresses by calculating a sparse collection of other covariance matrix entries following a sparsity pattern which is a subset of the non-zero entries of the Cholesky factor $R$. The number of entries computed, and thus the speed of the computation, depends heavily on the ordering of the optimization variables prior to Cholesky decomposition. Using a ordering aimed at reducing overall fill-in (such as Approximate Minimum Degree (AMD)) can lead to widely varied computation times when extracting the very small set of covariance matrix elements we need. We therefore re-order the matrix $H_{pp}$ prior to Cholesky decomposition with a constrained version of AMD [23]. This reordering scheme allows us to force the blocks of interest in the Cholesky factor to appear last in the permutation leading to a vast reduction in the number of sparse covariance matrix elements computed, and a large increase in speed. However, we pay for this ordering method in two ways. Firstly, constraining the position of some blocks of $I$ is likely to increase the overall fill-in of the Cholesky factor. Secondly, we perform a decomposition of $H_{pp}$ for each patch-pair candidate, instead of just once for all candidates, as is done in the original algorithm [22]. In our testing, despite these drawbacks, there was a substantial benefit to taking this approach.

E. Map Fusion

We frequently are required to fuse map patches, both at the request of the map maintenance module and for visualizing the current state of the manifold map. Given two patches to be fused $\pi_i$ and $\pi_j$ with a reference frames $M_i$ and $M_j$ the transformation between the patches and global map is then found

$$T_{M_iM_j} = (T_{GM_i})^{-1} \oplus T_{GM_j}. \quad (12)$$

We then transform the voxels in $\pi_j$, allocate new voxels in $\pi_i$ where needed and integrate their contributions using trilinear interpolation. For visualization of the whole manifold we repeat this process multiple times, fusing all patches into $\pi_1$.

V. Results

We evaluate the performance of our system on the publicly available KITTI dataset [24] as well as a number of our own indoor sequences.

A. KITTI

The KITTI dataset provides data from a car driving around a suburban environment equipped with wide base-line stereo cameras. In addition, the dataset includes accurate groundtruth trajectories and lidar sensor data. We demonstrate our system on drive 18, chosen as a challenging sequence because it contains long periods of exploration, significant drift, and place revisiting. To evaluate the quality of our reconstructions we approximate ground-truth 3D structure by building a TSDF map, and subsequently a mesh model, using lidar data and ground-truth poses. While both the ground-truth poses and lidar data will contain some degree of noise, we assume that errors are dominated by the tested mapping approach. We supply monochrome stereo camera images to the camera localization module, and pre-compute depth maps for use in 3D reconstruction using a standard and freely available Semi-Global Block Matching (SGBM) algorithm[1]. The proposed

image_undistort: https://github.com/ethz-asl/image_undistort
approach runs in real-time on a standard laptop CPU (Intel i7-6700HQ). Our TSDF resolution is set to 25 cm voxels.

|                      | Global Error (m) | Local Error (m) |
|----------------------|------------------|-----------------|
|                      | mean  | median | max  | mean  | median | max  |
| True Poses           | 0.27  | 0.14   | 3.81 | 0.28  | 0.18   | 3.90 |
| Global               | 1.28  | 0.95   | 15.67| 0.42  | 0.31   | 4.27 |
| Manifold             | 1.04  | 0.79   | 7.36 | 0.30  | 0.21   | 3.74 |

Table I: Reconstruction errors for various mapping methods evaluated using the global and local error metrics described in Section V-A.

To evaluate the performance of our system for correcting the dense map following loop closures we run our the system over the same sequence in three configurations: 1) building a single TSDF map using the stereo data and ground-truth poses, 2) building a single TSDF map using stereo data and poses supplied by ORB-SLAM2, 3) the proposed system. The first configuration represents an approximation of the best achievable error given the sensor setup while the second configuration represents the naive approach of not explicitly handling loop closures.

We quantitatively evaluate the performance of these configurations using two error measures. The first measure is the global metric accuracy of the reconstructed mesh and is calculated by determining the distance between each mesh vertex in the stereo construction to its closest neighbor in the ground-truth mesh. The map constructed using the manifold mapping system reduces the median error from 0.95 m, in the single TSDF map case, to 0.79 m, a 17% reduction. We quote the median here because stereo depth maps produce a significant number of outliers which skew the average, which might seem like a more natural measure. Nevertheless, we present the mean, median and maximum errors in Table I.

Typically, map consistency is more important than global metric accuracy in a robotic system, where for example map topology and traversability may be more of a concern than metric distances. We measure map consistency by measuring local metric accuracy under the assumption that areas of inconsistency are also likely to exhibit high local metric error. We construct the local error measure in the following way. First a map section is extracted by selecting a random mesh vertex and extracting all triangles with vertices within a radius, which we have selected for this experiment to be 50m. We then perform coarse-to-fine Iterative Closest Point (ICP) to align this mesh fragment to the ground-truth mesh. Once aligned, we calculate the point-to-point error between the aligned fragment and the ground-truth mesh. We repeat 100 times keeping a running average for the error at each vertex in the reconstructed mesh.

Figure 4 shows the submap covisibility adjacency matrix, and the matrix of the quality measures $q$ corresponding to all keyframe pairs. Off-diagonal areas of high value correspond to keyframes created when revisiting an area of the map. Figure 4 shows that by performing reconstruction using the proposed system the local error is significantly reduced in these locations.

The calculated local error metric for the tested reconstruction methods are shown in Table I. The use of a single TSDF mapping system produces a median local error of 0.31 m, 1.72 times the error produced using ground-truth poses. The proposed system produces a median error of 0.21 m, 1.16 times the minimum error. These results indicate that our system makes significant correction for local inconsistencies, and approaches the minimum achievable local error with our sensor setup.

Figure 4 shows two reconstructions colored by this local error measure. Patches of high local error are visible in the reconstruction produced by the naive system (Fig. 3a). These errors tend to occur in places that the car revisits after periods of exploration (indicated by the circles areas). This confirms what one might expect, during exploration the estimated pose is likely to drift. When the car returns to a previously visited area, but loop closure and bundle adjustment have not yet corrected the pose, depth frame integrations corrupt the map. Figure 3b shows that by performing reconstruction using the proposed system the local error is significantly reduced in these locations.
many common landmarks will have many indirect constrains linking them and therefore are likely to be well localized with respect to one another.

B. Indoor Datasets

We also report on reconstructions from two indoor datasets: jfloor_big and jfloor_small. These sequences are challenging because they contain: 1) long exploratory motion followed by very delayed loop closures, 2) extended operation in a confined space. These datasets cover two very different modes of operation. The datasets are recorded using stereo monochrome cameras from the vi-sensor [25] and depth maps generated using SGBM.

In the jfloor_big sequence a number of loops of one floor of an office building are traversed. Virtually the whole map is revisited at least once, often while traveling in opposite directions, resulting in significantly delayed loop closures. The maps constructed from this dataset are shown in Fig. 1a and Fig. 1b using the proposed mapping system with loop closure updates to the patches turned on and off respectively. The map in Fig. 1a shows significant inconsistencies, for example in corridor in the lower right of the reconstruction where two separate copies of a single corridor can be seen. This type of map inconsistency would present difficulties for robotic navigation. Figure 1a shows that these inconsistencies are corrected by the map maintenance performed by the proposed system.

Sequence jfloor_small contains image data from operation in a single room (Fig. 6). In this sequence the camera frequently observes an already mapped area, leading to many redundant views being generated in the manifold. The size of the map is shown in Fig. 5 plotted against the number of integrated frames for the proposed system with the patch fusion system described in IV-D turned on (solid line) and off (dashed line). The use of the map maintenance module reduces the size of the map by 51%. Furthermore, this figure is likely to increase with continued operation as without patch fusion the manifold size will increase without bound. Note that the map maintenance module only checks for fusion candidates following a loop closure, which gives rise to the jagged appearance of the map size.
VI. CONCLUSION

In this paper we have described a novel system for producing large-scale consistent dense 3D maps. Our system is based on maintaining a manifold map of the environment, comprised of overlapping TSDF subvolumes which together constitute the global map. We propose the incorporation of a novel systematic approach to limiting map growth by fusing redundant and well-localized subvolumes. Our evaluations on stereo camera data from the KITTI dataset, and on several self-collected datasets, show that the proposed system is able to correct for significant inconsistencies that stem from imperfect camera localization. In the KITTI dataset the proposed system reduces local map error from 171% of the minimum achievable error to 116%, when compared with a building a global TSDF. We show that the proposed system is able to correct for significant inconsistencies that stem from imperfect camera localization. In the KITTI dataset the proposed system reduces local map growth, reducing the map size by 51% during operation in an office environment where areas are frequently revisited. The ability to produce consistent and scalable dense maps, represents a step towards allowing robotic platforms to use detailed 3D maps in large scale environments. Lastly, we provide an open source implementation of the proposed system for use by the community (at the time of publication).

Figure 6: A reconstruction of a room in an office building. In this dataset the sensor observes the same area of the environment many times which results in the frequent patch fusions, limiting the growth of the map.

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