pySLAM: An Open-Source, Modular, and Extensible Framework for SLAM

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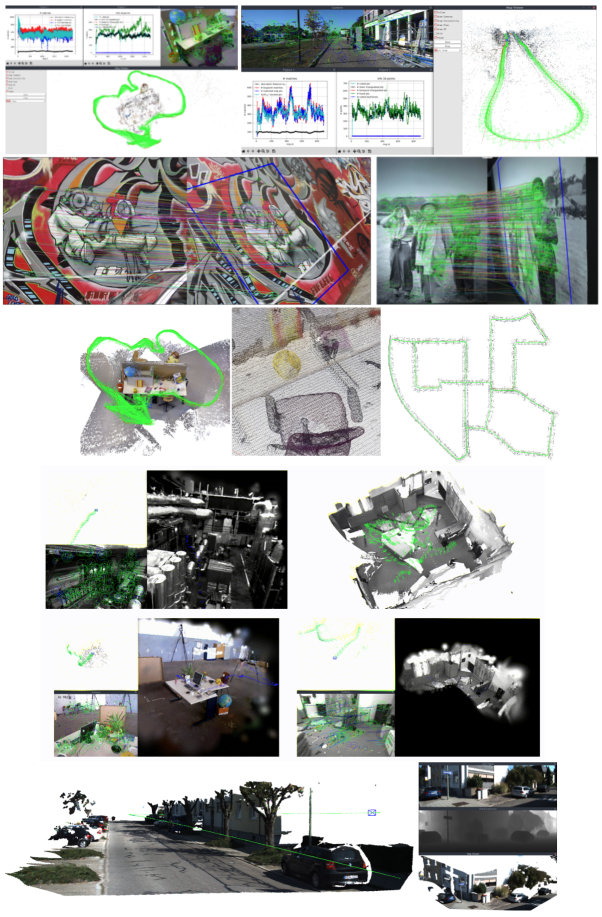
github.com/luigifreda/pyslam

Abstract

pySLAM is an open-source Python framework for Visual SLAM that supports monocular, stereo, and RGB-D camera inputs. It offers a flexible and modular interface, integrating a broad range of both classical and learning-based local features. The framework includes multiple loop closure strategies, a volumetric reconstruction pipeline, and support for depth prediction models. It also offers a comprehensive set of tools for experimenting with and evaluating visual odometry and SLAM modules. Designed for both beginners and experienced researchers, pySLAM emphasizes rapid prototyping, extensibility, and reproducibility across diverse datasets. Its modular architecture facilitates the integration of custom components and encourages research that bridges traditional and deep learning-based approaches. Community contributions are welcome, fostering collaborative development and innovation in the field of Visual SLAM. This document[1] presents the pySLAM framework, outlining its main components, features, and usage.



[1] You may find an updated version of this document at: github.com/luigifreda/pyslam/blob/master/docs/tex/document.pdf

Contents

1 Introduction

pySLAM is an open-source framework designed to accelerate research and development in Visual SLAM (Simultaneous Localization and Mapping) and Spatial AI. It originated from a practical need identified during the development of a SLAM/Spatial AI course: The absence of a unified, accessible, and extensible SLAM ecosystem in C++ and Python. The project was driven by several foundational motivations, including the desire to rapidly prototype and evaluate both *classical* and *learning-based* features within complete VO/SLAM pipelines, ensure reproducibility across a wide range of datasets, and significantly lower the entry barrier for newcomers to the field.

A key decision behind pySLAM development was the choice of *Python* as its primary language. Compared to C++, Python enables faster experimentation and benefits from a mature and expanding ecosystem of deep learning tools and research-oriented APIs. This choice aligns with current trends in computer vision and robotics research, where rapid prototyping and flexible experimentation are essential.

However, designing a modern SLAM framework in Python presents several challenges. The SLAM landscape is highly fragmented – across feature types, datasets, programming languages (Python vs. C++), and development environments (virtual environments, Docker, versioning issues). Deep learning integration further complicates matters due to backend fragmentation (e.g., PyTorch vs. TensorFlow). These inconsistencies often lead to reproducibility bottlenecks and high barriers to experimental research, where setting up a functional baseline can become more laborious than the research itself.

To address these issues, pySLAM is built on several key design principles. *Modularity* is central: components such as local/global features, loop closure mechanisms, semantic mapping, and volumetric integration can be easily swapped or extended. This architecture supports the use of interchangeable baselines, enabling researchers to plug-and-play with different configurations depending on their goals. *Extensibility* is facilitated through a base-class architecture that allows new components to be integrated with minimal friction, making pySLAM a flexible platform for benchmarking and algorithm development.

In terms of usability, pySLAM emphasizes simplicity in the build and deployment process.. It supports a unified Python environment compatible with *conda*, *pyenv*, and *pixi*, and offers a one-command installation process that covers setup and dataset acquisition. Cross-platform compatibility (Linux, macOS, Windows with WSL2) and full source accessibility further enhance its utility for both academic and industrial use.

Another cornerstone of the framework is standardized dataset handling. By providing a unified interface to multiple datasets, pySLAM encourages *reproducibility* and *reusability*. It supports consistent data loading, map state saving/loading, and automatic generation of evaluation metrics – including final and online trajectory estimation – thus enabling robust comparison between algorithms.

Functionally, pySLAM supports the full visual SLAM pipeline with monocular, stereo, and RGB-D configurations. It accommodates both traditional local features and deep-learning-based methods, and includes loop closure detection integrated with optimization backends like g2o and GTSAM. The framework also supports 3D reconstruction via TSDF and emerging techniques like Gaussian Splatting, and integrates deep learning models for depth prediction and semantic scene understanding.

Beyond SLAM, pySLAM also provides a unified *ScenefromViews* architecture for modern multi-view 3D reconstruction starting from a collection of images.

Together, these capabilities position pySLAM as a powerful research toolkit – aiming to be a "Swiss army knife" for SLAM development, evaluation, and education. By streamlining reproducibility, supporting modular experimentation, and lowering the technical threshold for entry, pySLAM addresses some of the most persistent challenges in contemporary SLAM research.

The objective of this document is to present the pySLAM framework, its main features, and usage[2].

2 Main Features

pySLAM provides a python implementation of a *Visual SLAM* pipeline that supports **monocular**, **stereo** and **RGBD** cameras. It offers the following **features** in a single python environment:

- A wide range of classical and modern **local features** with a convenient interface for their integration.
- Various loop closing methods, including **descriptor aggregators** such as visual Bag of Words (BoW, iBow), Vector of Locally Aggregated Descriptors (VLAD), and modern **global descriptors** (image-wise descriptors).

[2] You may find an updated version of this document at:
github.com/luigifreda/pyslam/blob/master/docs/tex/document.pdf

- A **volumetric reconstruction pipeline** that processes available depth and color images with volumetric integration and provides an output dense reconstruction. This can use **TSDF** with voxel hashing or incremental **Gaussian Splatting**.
- Integration of **depth prediction models** within the SLAM pipeline. These include DepthPro, DepthAnythingV2, RAFT-Stereo, CREStereo, MASt3R, MVDUSt3R, etc.
- A suite of segmentation models for **semantic understanding** of the scene, such as DeepLabv3, Segformer, CLIP, EOV-Seg, Detic, and ODISE.
- A **Scene from Views** module providing a unified interface for 3D scene reconstruction from multiple views, supporting models such as DUSt3R, MASt3R, Depth Anything V3, MV-DUSt3R, and VGGT.
- A **C++ Core** module for high-performance sparse SLAM, with pybind11 bindings enabling zero-copy data exchange between Python and C++.
- Additional tools for VO (Visual Odometry) and SLAM, with built-in support for both **g2o** and **GTSAM**, along with custom Python bindings for features not available in the original libraries
- Built-in support for over **10 dataset types**. The list is currently growing.

pySLAM serves as a flexible baseline framework to experiment with VO/SLAM techniques, *local features*, *descriptor aggregators*, *global descriptors*, *volumetric integration*, *depth prediction*, *semantic mapping*, *scene from views*, and *C++ core*. It allows to explore, prototype and develop VO/SLAM pipelines. pySLAM is a research framework and a work in progress. It is not optimized for real-time performance.

3 Overview

3.1 Main Scritps

A convenient entry point is the following collection of **main scripts**:

- `main_vo.py` combines the simplest VO ingredients without performing any image point triangulation or windowed bundle adjustment. At each step k, `main_vo.py` estimates the current camera pose C_k with respect to the previous one C_{k-1}. The inter-frame pose estimation returns $[R_{k-1,k}, t_{k-1,k}]$ with $\|t_{k-1,k}\| = 1$. With this very basic approach, you need to use a ground truth in order to recover a correct inter-frame scale s and estimate a valid trajectory by composing $C_k = C_{k-1}[R_{k-1,k}, st_{k-1,k}]$. This script is a first start to understand the basics of inter-frame feature tracking and camera pose estimation.
- `main_slam.py` adds feature tracking along multiple frames, point triangulation, keyframe management, bundle adjustment, loop closing, dense mapping and depth inference in order to estimate the camera trajectory and build both a sparse and dense map. It's a full SLAM pipeline and includes all the basic and advanced blocks which are necessary to develop a real visual SLAM pipeline.
- `main_feature_matching.py` shows how to use the basic feature tracker capabilities (*feature detector* + *feature descriptor* + *feature matcher*) and allows to test the different available local features.
- `main_depth_prediction.py` shows how to use the available depth inference models to get depth estimations from input color images.
- `main_map_viewer.py` reloads a saved map and visualizes it. Further details on how to save a map here.
- `main_map_dense_reconstruction.py` reloads a saved map and uses a configured volumetric integrator to obtain a dense reconstruction (see here).
- `main_slam_evaluation.py` enables automated SLAM evaluation by executing `main_slam.py` across a collection of datasets and configuration presets (see here).
- `main_scene_from_views.py` demonstrates how to use the Scene from Views factory for 3D scene reconstruction from multiple views using various reconstruction models (see here).

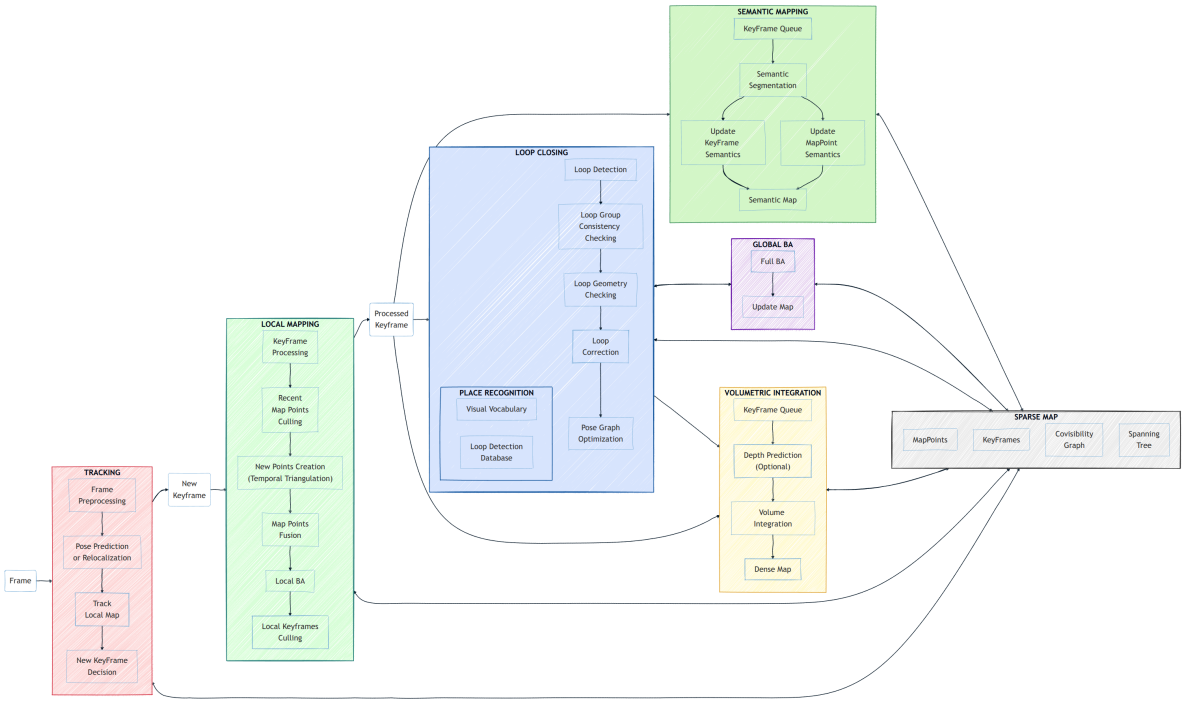


Figure 1: SLAM workflow.

3.2 System overview

This section presents some diagram sketches that provide an overview of the main workflow, system components, and class relationships/dependencies. To make the diagrams more readable, some minor components and arrows have been omitted.

SLAM Workflow and Components

Fig. 1 illustrates the SLAM workflow, which is composed of six main parallel processing modules:

- *Tracking*: estimates the camera pose for each incoming frame by extracting and matching local features to the local map, followed by minimizing the reprojection error through motion-only Bundle Adjustment (BA). It includes components such as pose prediction (or relocalization), feature tracking, local map tracking, and keyframe decision-making.
- *Local Mapping*: updates and refines the local map by processing new keyframes. This involves culling redundant map points, creating new points via temporal triangulation, fusing nearby map points, performing Local BA, and pruning redundant local keyframes.
- *Loop Closing*: detects and validates loop closures to correct drift accumulated over time. Upon loop detection, it performs loop group consistency checks and geometric verification, applies corrections, and then launches Pose Graph Optimization (PGO) followed by a full Global Bundle Adjustment (GBA). Loop detection itself is delegated to a parallel process, the *Loop Detector*, which operates independently for better responsiveness and concurrency.
- *Global Bundle Adjustment*: triggered by the Loop Closing module after PGO, this step globally optimizes the trajectory and the sparse structure of the map to ensure consistency across the entire sequence.
- *Volumetric Integration*: uses the keyframes, with their estimated poses and back-projected point clouds, to reconstruct a dense 3D map of the environment. This module optionally integrates predicted depth maps and maintains a volumetric representation such as a TSDF [15] or incremental Gaussian Splatting-based volume [37, 21].
- *Semantic Mapping*: enriches the SLAM map with dense semantic information by applying pixel-wise segmentation to selected keyframes. Semantic predictions are fused across views to assign semantic labels or descriptors to keyframes and map points. The module operates in parallel, consuming keyframes and associated image data from a queue, applying a configured semantic segmentation model, and updating the map with fused semantic features. This enables advanced downstream tasks such as semantic navigation, scene understanding, and category-level mapping.

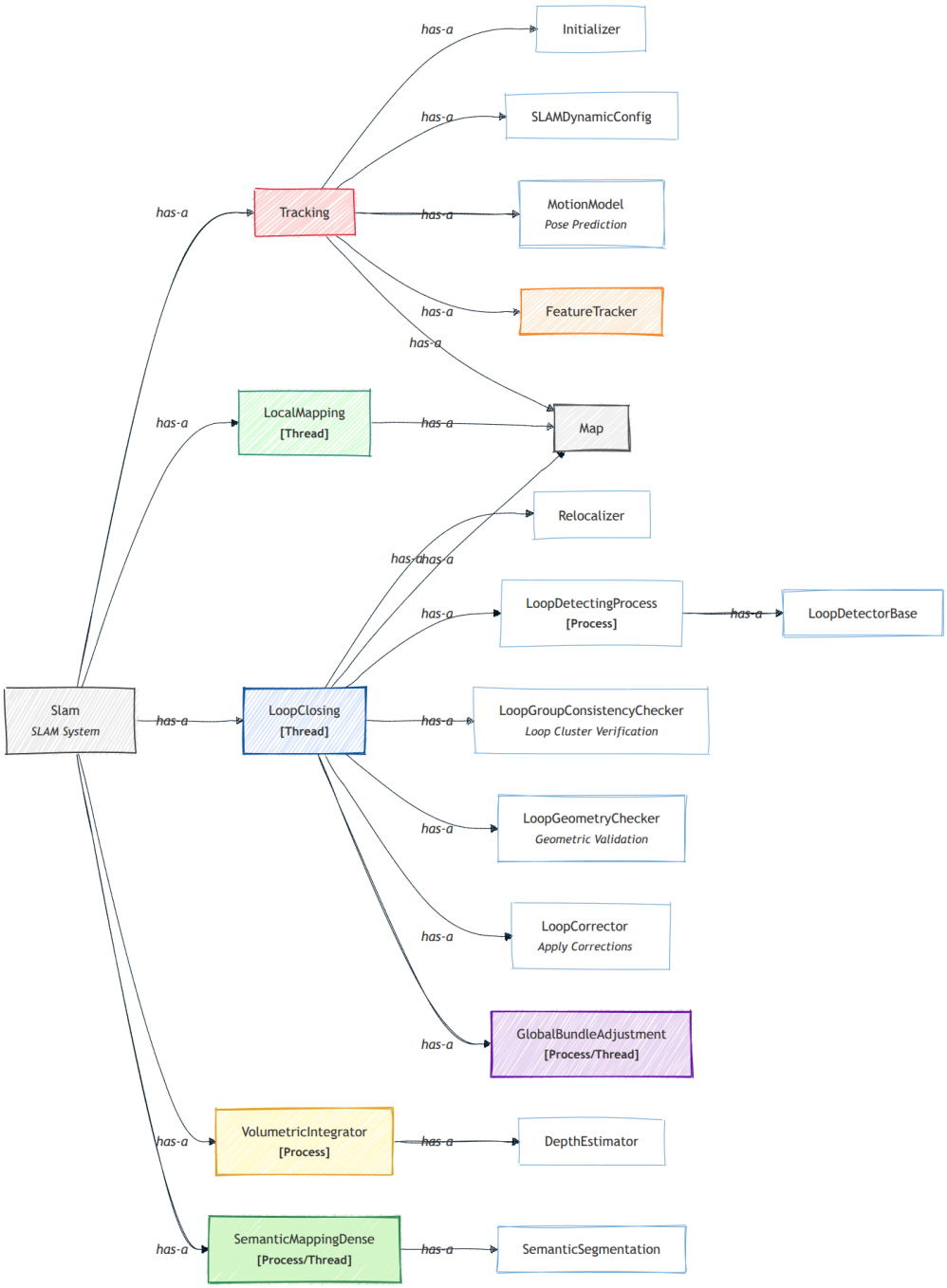


Figure 2: SLAM components.

The first four modules follow the established PTAM [22] and ORB-SLAM [43] paradigm. Here, the *Tracking* module serves as the front-end, while the remaining modules operate as part of the back-end.

In parallel, the system constructs two types of maps:

- a *sparse map* $\mathcal{M}_s = (\mathcal{K}, \mathcal{P})$, composed of a set of keyframes $\mathcal{K}$ and 3D points $\mathcal{P}$ derived from matched features;
- a *volumetric map* (or dense map) $\mathcal{M}_v$, constructed by the Volumetric Integration module, which fuses back-projected point clouds from the keyframes $\mathcal{K}$ into a dense 3D model.

To ensure consistency between the sparse and volumetric representations, the volumetric map is updated or re-integrated whenever global pose adjustments occur (e.g., after loop closures).

Fig. 2 details the internal components and interactions of the above modules. In certain cases, **processes** are

employed instead of **threads**. This is due to Python's Global Interpreter Lock (GIL), which prevents concurrent execution of multiple threads in a single process. The use of multiprocessing circumvents this limitation, enabling true parallelism at the cost of some inter-process communication overhead (e.g., via pickling). For an insightful discussion, see this related post.

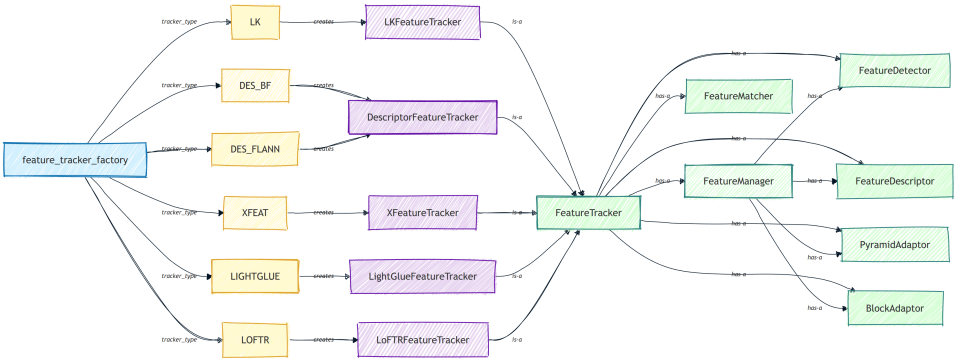


Figure 3: Feature tracker.

3.3 Main SLAM System Components

Feature Tracker

The *Feature Tracker* consists of the following key sub-components:

- *Feature Manager*: Manages local feature operations. It includes the `FeatureDetector`, `FeatureDescriptor`, and adaptors for pyramid management and image tiling.
  - *Feature Detector*: Identifies salient and repeatable keypoints in the image, such as corners or blobs, which are likely to be robust under viewpoint and illumination changes.
  - *Feature Descriptor*: Computes a distinctive descriptor for each detected keypoint, encoding its local appearance to enable robust matching across frames. Examples include ORB [55], SIFT [31], or SuperPoint [14] descriptors.
- *Feature Matcher*: Establishes correspondences between features in successive frames (or stereo pairs) by comparing their descriptors or directly inferring matches from image content. Matching can be performed using brute-force, k-NN with ratio test, or learned matching strategies. Refere to Sect. 3.3 for futher details.

Sect. 5.1 lists the supported local feature extractors and detectors.

The diagram in Fig. 3 presents the architecture of the *Feature Tracker* system. It is structured around a `feature_tracker_factory`, which instantiates specific tracker types such as `LK`, `DES_BF`, `DES_FLANN`, `XFEAT`, `LIGHTGLUE`, and `LOFTR`. Each tracker type creates a corresponding implementation (e.g., `LKFeatureTracker`, `DescriptorFeatureTracker`, etc.), all of which inherit from a common `FeatureTracker` interface.

The `FeatureTracker` class is composed of several key sub-components, including a `FeatureManager`, `FeatureDetector`, `FeatureDescriptor`, `PyramidAdaptor`, `BlockAdaptor`, and `FeatureMatcher`. The `FeatureManager` also encapsulates instances of the detector, descriptor, and adaptors, highlighting the modular and reusable design of the tracking pipeline.

Feature Matcher

The diagram in Fig. 4 illustrates the architecture of the *Feature Matcher* module. At its core is the `feature_matcher_factory`, which instantiates matchers based on a specified `matcher_type`, such as `BF`, `FLANN`, `XFEAT`, `LIGHTGLUE`, and `LOFTR`. Each of these creates a corresponding matcher implementation (e.g., `BfFeatureMatcher`, `FlannFeatureMatcher`, etc.), all inheriting from a common `FeatureMatcher` interface.

The `FeatureMatcher` class encapsulates several configuration parameters and components, including the matcher engine (`cv2.BFMatcher`, `FlannBasedMatcher`, `xfeat.XFeat`, etc.), as well as the `matcher_type`, `detector_type`, `descriptor_type`, `norm_type`, and `ratio_test` fields. This modular structure supports extensibility and facilitates switching between traditional and learning-based feature matching backends.

The Section 5.2 reports a list of supported feature matchers.

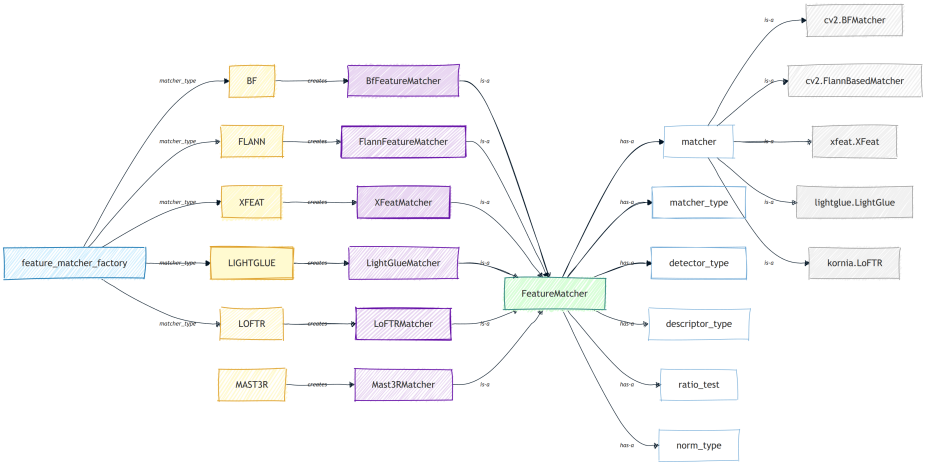


Figure 4: Feature matcher.

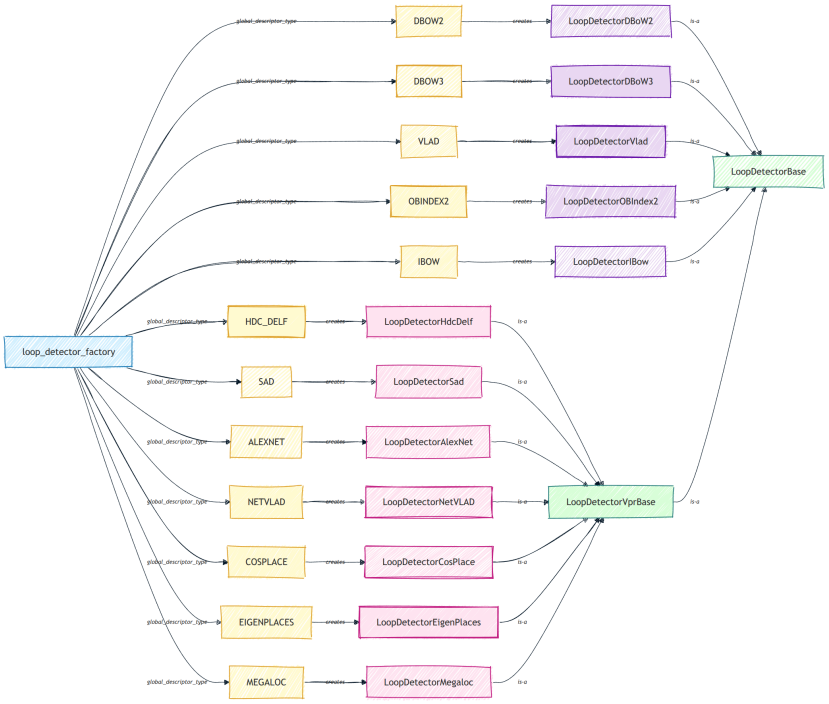


Figure 5: Loop detector.

Loop Detector

The diagram in Fig. 5 shows the architecture of the *Loop Detector* component. A central `loop_detector_factory` instantiates loop detectors based on the selected `global_descriptor_type`, which may include traditional descriptors (e.g., `DBOW2`, `VLAD`, `IBOW`) or deep learning-based embeddings (e.g., `NetVLAD`, `CosPlace`, `EigenPlaces`).

Each descriptor type creates a corresponding loop detector implementation (e.g., `LoopDetectorDBoW2`, `LoopDetectorNetVLAD`), all of which inherit from a base class hierarchy. Traditional methods inherit directly from `LoopDetectorBase`, while deep learning-based approaches inherit from `LoopDetectorVprBase`, which itself extends `LoopDetectorBase`. This design supports modular integration of diverse place recognition techniques within a unified loop closure framework.

The Section 5.3 reports a list of supported loop closure methods with the adopted global descriptors and local descriptor aggregation methods.

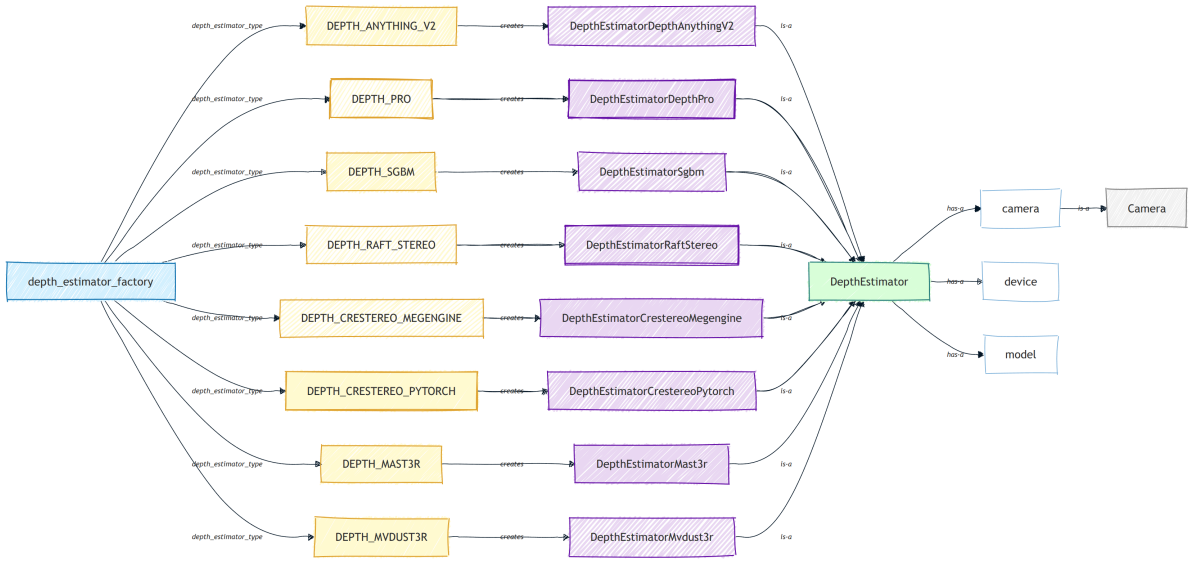


Figure 6: Depth estimator.

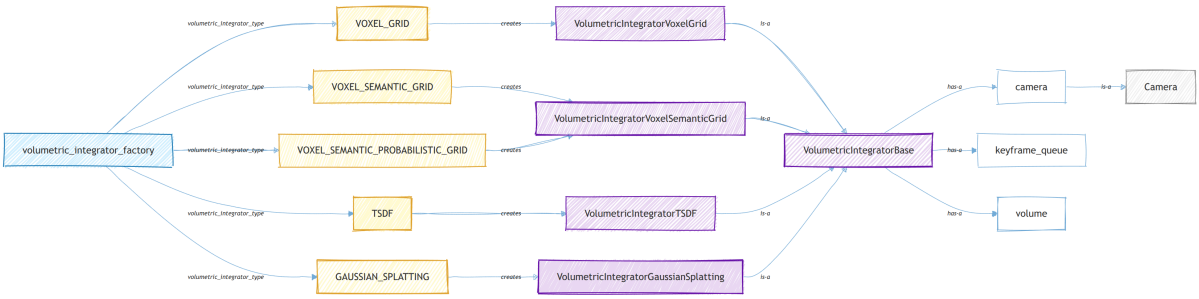


Figure 7: Volumetric integrator.

Depth Estimator

The diagram in Fig. 6 illustrates the architecture of the *Depth Estimator* module. A central `depth_estimator_factory` creates instances of various depth estimation backends based on the selected `depth_estimator_type`, including both traditional and learning-based methods such as `DEPTH_SGBM`, `DEPTH_RAFT_STEREO`, `DEPTH_ANYTHING_V2`, `DEPTH_MAST3R`, and `DEPTH_MVDUST3R`.

Each estimator type instantiates a corresponding implementation (e.g., `DepthEstimatorSgbm`, `DepthEstimator-CrestereoMegengine`, etc.), all inheriting from a common `DepthEstimator` interface. This base class encapsulates shared dependencies such as the `camera`, `device`, and `model` components, allowing for modular integration of heterogeneous depth estimation techniques across stereo, monocular, and multi-view pipelines.

The Section 5.4 reports a list of supported depth estimation/prediction models.

Volumetric Integrator

The diagram in Fig. 7 illustrates the structure of the *Volumetric Integrator* module. At its core, the `volumetric_integrator_factory` generates specific volumetric integrator instances based on the selected `volumetric_integrator_type`, such as `VOXEL_GRID`, `VOXEL_SEMANTIC_GRID`, `VOXEL_SEMANTIC_PROBABILISTIC_GRID`, `TSDF`, and `GAUSSIAN_SPLATTING`.

Each type instantiates a dedicated implementation (e.g., `VolumetricIntegratorVoxelGrid`, `VolumetricIntegrator-VoxelSemanticGrid`, `VolumetricIntegratorTSDF`, `VolumetricIntegratorGaussianSplatting`), which inherits from a common `VolumetricIntegratorBase`. This base class encapsulates key components including the `camera`, a `keyframe_queue`, and the `volume`, enabling flexible integration of various 3D reconstruction methods within a unified pipeline.

The Section 5.5 reports a list of supported volume integration methods.

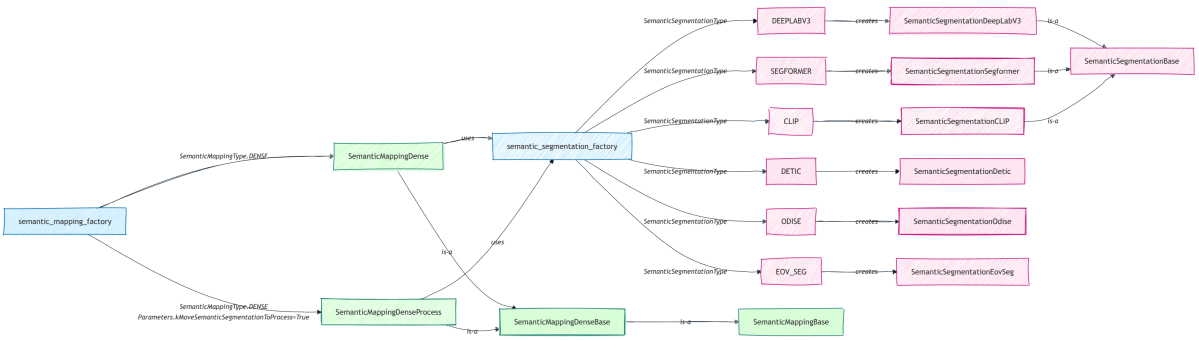


Figure 8: Semantic Mapping.

Semantic Mapping

The diagram in Fig. 8 outlines the architecture of the *Semantic Mapping* module. At its core is the `semantic_mapping_factory`, which creates semantic mapping instances according to the selected `semantic_mapping_type`. Currently, the supported type is `DENSE`, which instantiates either the `SemanticMappingDense` class or the `SemanticMappingDenseProcess` class if

```
Parameters.kSemanticMappingMoveSemanticSegmentationToSeparateProcess=True
```

Both these classes extend `SemanticMappingDenseBase` and runs asynchronously in a dedicated thread to process keyframes as they become available. In particular, the `SemanticMappingDenseProcess` class offloads semantic segmentation inference to a separate process, thereby making better use of CPU core parallelism.

Both `SemanticMappingDense` and `SemanticMappingDenseProcess` integrate semantic information into the SLAM map by leveraging per-frame predictions from a semantic segmentation model. The segmentation model is instantiated via the `semantic_segmentation_factory`, based on the selected `semantic_segmentation_type`. Supported segmentation backends include `DEEPLABV3`, `SEGFORMER`, `CLIP`, `EOV_SEG`, `DETIC`, and `ODISE`, each of which corresponds to a dedicated class (`SemanticSegmentationDeepLabV3`, `SemanticSegmentationSegformer`, `SemanticSegmentationCLIP`, `SemanticSegmentationEovSeg`, `SemanticSegmentationDetic`, `SemanticSegmentationOdise`) inheriting from the shared `SemanticSegmentationBase`.

The system supports multiple semantic feature representations – such as categorical labels, probability vectors, and high-dimensional feature embeddings – and fuses them into the map using configurable methods like count-based fusion, Bayesian fusion, or feature averaging.

This modular design decouples semantic segmentation from mapping logic, enabling flexible combinations of segmentation models, datasets (e.g., `NYU40`, `Cityscapes`), and fusion strategies. It also supports customization via configuration files or programmatic APIs for dataset-specific tuning or deployment.

The Section 4.3 provides a list of supported semantic segmentation methods. A more in-depth presentation of the semantic mapping module is provided in [41].

3.4 3D Scene from Views

The diagram in Fig. 9 illustrates the architecture of the *Scene from Views* module, which provides a unified interface for 3D scene reconstruction from multiple views. At its core, the `scene_from_views_factory` instantiates specific reconstruction models based on the selected `SceneFromViewsType`, such as `DUST3R`, `MAST3R`, `DEPTH_ANYTHING_V3`, `MVDUST3R`, `VGGT`, and `VGGT_ROBUST`.

Each type creates a corresponding implementation (e.g., `SceneFromViewsDust3r`, `SceneFromViewsMast3r`, `SceneFromViewsDepthAnythingV3`, `SceneFromViewsMvdust3r`, `SceneFromViewsVggt`, `SceneFromViewsVggtRobust`), all inheriting from a common `SceneFromViewsBase`. This base class implements a unified three-step reconstruction pipeline: `preprocess_images()` prepares input images for the specific model, `infer()` runs model inference, and `postprocess_results()` converts raw model output to a standardized `SceneFromViewsResult` format containing merged point clouds, meshes, camera poses, and optional depth maps or intrinsics.

The module supports both pairwise models (DUSt3R, MASt3R) that process image pairs and perform global alignment, as well as multi-view models (MV-DUSt3R, VGGT) that process multiple views simultaneously in a single forward pass. This modular design enables flexible integration of diverse 3D reconstruction techniques while maintaining a consistent API across different model architectures.

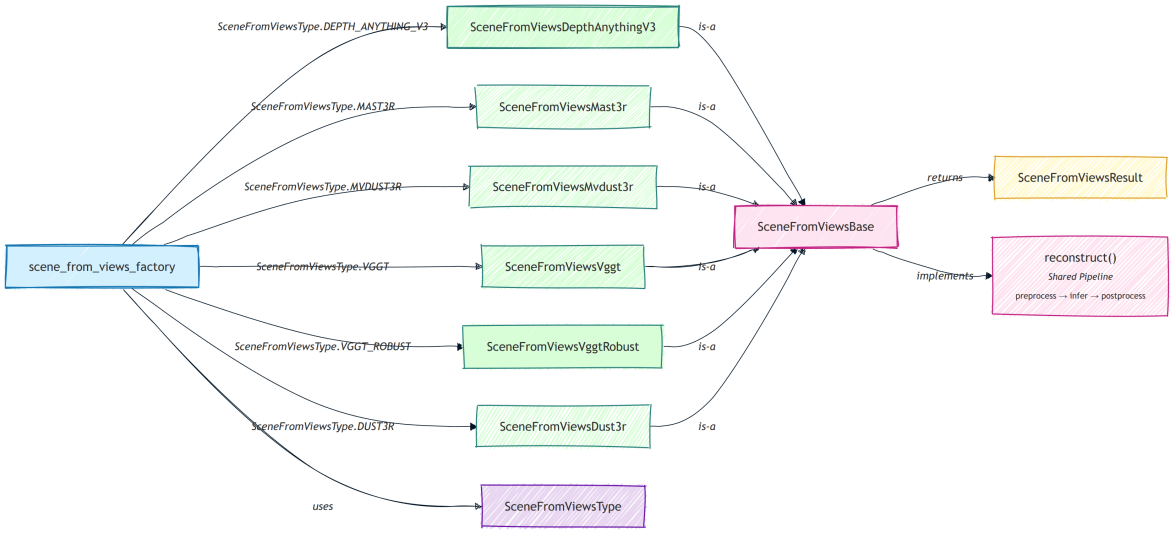


Figure 9: *SceneFromViews* architecture.

4 Usage

Open a new terminal and start experimenting with the scripts. In each new terminal you are supposed to start with this command:

```
$ . pyenv-activate.sh   #  Activate pyslam python virtual environment. This is only needed once in a new terminal.
```

The file config.yaml can be used as a unique entry-point to configure the system and its global configuration parameters contained in pyslam/config_parameters.py. Further information on how to configure pySLAM are provided here.

Visual odometry

The basic **Visual Odometry** (VO) can be run with the following commands:

```
$ . pyenv-activate.sh   #  Activate pyslam python virtual environment. This is only needed once in a new terminal.
$ ./main_vo.py
```

By default, the script processes a KITTI video (available in the folder `data/videos`) by using its corresponding camera calibration file (available in the folder `settings`), and its groundtruth (available in the same `data/videos` folder). If matplotlib windows are used, you can stop `main_vo.py` by clicking on one of them and pressing the key 'Q'. As explained above, this very *basic* script `main_vo.py` **strictly requires a ground truth**. Now, with RGBD datasets, you can also test the **RGBD odometry** with the classes `VisualOdometryRgbd` or `VisualOdometryRgbdTensor` (ground truth is not required here).

Full SLAM

Similarly, you can test the **full SLAM** by running `main_slam.py`:

```
$ . pyenv-activate.sh   #  Activate pyslam python virtual environment. This is only needed once in a new terminal.
$ ./main_slam.py
```

This will process the same default KITTI video (available in the folder `data/videos`) by using its corresponding camera calibration file (available in the folder `settings`). You can stop it by clicking on one of the opened windows and pressing the key 'Q' or closing the 3D pangolin GUI.

Selecting a dataset and different configuration parameters

The file config.yaml can be used as a unique entry-point to configure the system, the target dataset and its global configuration parameters set in pyslam/config_parameters.py. To process a different **dataset** with both VO and SLAM scripts, you need to update the file config.yaml:

- Select your dataset `type` in the section `DATASET` (further details in the section *Datasets* below for further details). This identifies a corresponding dataset section (e.g. `KITTI_DATASET`, `TUM_DATASET`, etc).

- Select the `sensor_type` (`mono`, `stereo`, `rgbd`) in the chosen dataset section.
- Select the camera `settings` file in the dataset section (further details in the section *Camera Settings* below).
- Set the `groudtruth_file` accordingly. Further details in the section *Datasets* below (see also the files `pyslam/io/ground_truth.py` and `pyslam/io/convert_groundtruth_to_simple.py`).

You can use the section `GLOBAL_PARAMETERS` of the file config.yaml to override the global configuration parameters set in pyslam/config_parameters.py. This is particularly useful when running a SLAM evaluation.

4.1 Feature tracking

If you just want to test the basic feature tracking capabilities (*feature detector* + *feature descriptor* + *feature matcher*) and get a taste of the different available local features, run

```
$ . pyenv-activate.sh   # Activate pyslam python virtual environment. This is only needed once in a new terminal.
$./main_feature_matching.py
```

In any of the above scripts, you can choose any detector/descriptor among *ORB*, *SIFT*, *SURF*, *BRISK*, *AKAZE*, *SuperPoint*, etc. (see the section *Supported Local Features* below for further information).

Some basic examples are available in the subfolder `test/cv`. In particular, as for feature detection/description, you may want to take a look at test/cv/test_feature_manager.py too.

4.2 Loop closing

Many loop closing methods are available, combining different aggregation methods and global descriptors.

While running full SLAM, loop closing is enabled by default and can be disabled by setting `kUseLoopClosing=False` in `pyslam/config_parameters.py`. Different configuration options `LoopDetectorConfigs` can be found in pyslam/loop_closing/loop_detector_configs.py: Code comments provide additional useful details.

One can start experimenting with loop closing methods by using the examples in `test/loopclosing`. The example test/loopclosing/test_loop_detector.py is the recommended entry point.

Vocabulary management

`DBoW2`, `DBoW3`, and `VLAD` require **pre-trained vocabularies**. ORB-based vocabularies are automatically downloaded into the `data` folder (see pyslam/loop_closing/loop_detector_configs.py).

To create a new vocabulary, follow these steps:

1. **Generate an array of descriptors**: Use the script `test/loopclosing/test_gen_des_array_from_imgs.py` to generate the array of descriptors that will be used to train the new vocabulary. Select your desired descriptor type via the tracker configuration.
2. **DBOW vocabulary generation**: Train your target DBOW vocabulary by using the script `test/loopclosing/test_gen_dbow_voc_from_des_array.py`.
3. **VLAD vocabulary generation**: Train your target VLAD "vocabulary" by using the script `test/loopclosing/test_gen_vlad_voc_from_des_array.py`.

Once you have trained the vocabulary, you can add it in pyslam/loop_closing/loop_detector_vocabulary.py and correspondingly create a new loop detector configuration in pyslam/loop_closing/loop_detector_configs.py that uses it.

Vocabulary-free loop closing

Most methods do not require pre-trained vocabularies. Specifically:

- `iBoW` and `OBindex2`: These methods incrementally build bags of binary words and, if needed, convert (front-end) non-binary descriptors into binary ones.
- Others: Methods like `HDC_DELF`, `SAD`, `AlexNet`, `NetVLAD`, `CosPlace`, and `EigenPlaces` directly extract their specific **global descriptors** and process them using dedicated aggregators, independently from the used front-end descriptors.

As mentioned above, only `DBoW2`, `DBoW3`, and `VLAD` require pre-trained vocabularies.

Verify your loop detection configuration and verify vocabulary compability

Loop detection method based on a pre-trained vocabulary

When selecting a **loop detection method based on a pre-trained vocabulary** (such as `DBoW2`, `DBoW3`, and `VLAD`), ensure the following:

1. The back-end and the front-end are using the same descriptor type (this is also automatically checked for consistency) or their descriptor managers are independent (see further details in the configuration options `LoopDetectorConfigs` available in pyslam/loop_closing/loop_detector_configs.py).
2. A corresponding pre-trained vocubulary is available. For more details, refer to the vocabulary management section.

Missing vocabulary for the selected front-end descriptor type

If you lack a compatible vocabulary for the selected front-end descriptor type, you can follow one of these options:
1. Create and load the vocabulary (refer to the vocabulary management section).
2. Choose an `*_INDEPENDENT` loop detector method, which works with an independent local_feature_manager.
3. Select a vocabulary-free loop closing method.

See the file pyslam/loop_closing/loop_detector_configs.py for further details.

4.3 Volumetric reconstruction

Dense reconstruction while running SLAM

The SLAM back-end hosts a volumetric reconstruction pipeline. This is disabled by default. You can enable it by setting `kDoVolumetricIntegration=True` and selecting your preferred method `kVolumetricIntegrationType` in `pyslam/config_parameters.py`. At present, the following methods are available: `VOXEL_GRID`, `VOXEL_SEMANTIC_GRID`, `VOXEL_SEMANTIC_PROBABILISTIC_GRID`, `TSDF`, and `GAUSSIAN_SPLATTING` (see pyslam/dense/volumetric_integrator_factory.py). Note that you need CUDA in order to run `GAUSSIAN_SPLATTING` method.

The volumetric reconstruction pipeline works with:

- RGBD datasets
- When a depth estimator is used
  - in the back-end with STEREO datasets (you can't use depth prediction in the back-end with MONOCULAR datasets, further details here)
  - in the front-end (to emulate an RGBD sensor) and a depth prediction/estimation gets available for each processed keyframe.

To obtain a mesh as output, set `kVolumetricIntegrationExtractMesh=True` in `config_parameters.py`.

Reload a saved sparse map and perform dense reconstruction

Use the script `main_map_dense_reconstruction.py` to reload a saved sparse map and perform dense reconstruction by using its posed keyframes as input. You can select your preferred dense reconstruction method directly in the script.

- To check what the volumetric integrator is doing, run in another shell `tail -f logs/volumetric_integrator.log` (from repository root folder).
- To save the obtained dense and sparse maps, press the `Save` button on the GUI.

Reload and check your dense reconstruction

You can check the output pointcloud/mesh by using CloudCompare.

In the case of a saved Gaussian splatting model, you can visualize it by:

1. Using the superslat editor (drag and drop the saved Gaussian splatting `.ply` pointcloud in the editor interface).
2. Getting into the folder `test/gaussian_splatting` and running:

```
$ python test_gsm.py --load <gs_checkpoint_path>
```

The directory `<gs_checkpoint_path>` is expected to have the following structure:

```
+-- gs_checkpoint_path
|   +-- pointcloud          # folder containing different subfolders, each one with a saved .ply
|                           # encoding the Gaussian splatting model at a specific iteration/checkpoint
|   +-- last_camera.json
|   +-- config.yml
```

Controlling the spatial distribution of keyframe FOV centers

If you are targeting volumetric reconstruction while running SLAM, you can enable a **keyframe generation policy** designed to manage the spatial distribution of keyframe field-of-view (FOV) centers. The *FOV center* of a camera is defined as the backprojection of its image center, computed using the median depth of the frame. With this policy, a new keyframe is generated only if its FOV center lies beyond a predefined distance from the nearest existing keyframe's FOV center. You can enable this policy by setting the following parameters in the yaml setting:

```
KeyFrame.useFovCentersBasedGeneration: 1  # compute 3D fov centers of camera frames by using median depth
                                          # use their distances to control keyframe generation
KeyFrame.maxFovCentersDistance: 0.2       # max distance between fov centers in order to generate a keyframe
```

Depth prediction

The available depth prediction models can be utilized both in the SLAM back-end and front-end.

- **Back-end**: Depth prediction can be enabled in the volumetric reconstruction pipeline by setting the parameter `kVolumetricIntegrationUseDepthEstimator=True` and selecting your preferred `kVolumetricIntegrationDepthEstimatorType` in `pyslam/config_parameters.py`.
- **Front-end**: Depth prediction can be enabled in the front-end by setting the parameter `kUseDepthEstimatorInFrontEnd` in `pyslam/config_parameters.py`. This feature estimates depth images from input color images to emulate a RGBD camera. Please, note this functionality is still *experimental* at present time [WIP].

Notes:

- In the case of a **monocular SLAM**, do NOT use depth prediction in the back-end volumetric integration: The SLAM (fake) scale will conflict with the absolute metric scale of depth predictions. With monocular datasets, you can enable depth prediction to run in the front-end (to emulate an RGBD sensor).
- Depth inference may be very slow (for instance, with DepthPro it takes ~1s per image on a typical machine). Therefore, the resulting volumetric reconstruction pipeline may be very slow.

Refer to the file `pyslam/depth_estimation/depth_estimator_factory.py` for further details. Both stereo and monocular prediction approaches are supported. You can test depth prediction/estimation by using the script `main_depth_prediction.py`.

Semantic mapping

The semantic mapping pipeline can be enabled by setting the parameter `kDoSparseSemanticMappingAndSegmentation=True` in `config_parameters.py`. The best way of configuring the semantic mapping module used is to modify it in `semantic_mapping_configs.py`.

Different semantic mapping methods are available Currently, we support semantic mapping using dense semantic segmenetation.

- `DEEPLABV3`: from `torchvision`, pre-trained on COCO/VOC.
- `SEGFORMER`: from `transformers`, pre-trained on Cityscapes or ADE20k.
- `CLIP`: from `f3rm` package for open-vocabulary support.
- `EOV_SEG`: open-vocabulary panoptic segmentation model.
- `DETIC`: open-vocabulary object detection and segmentation model.
- `ODISE`: open-vocabulary diffusion-based panoptic segmentation model.

Semantic features are assigned to keypoints on the image and fused into map points. The semantic features can be:

- *Labels*: categorical labels as numbers.
- *Probability vectors*: probability vectors for each class.

- *Feature vectors*: feature vectors obtained from an encoder. This is generally used for open vocabulary mapping.

4.4 C++ Core for Sparse SLAM

The system provides a modular **sparse-SLAM core**, implemented in **both Python and C++** (with custom pybind11 bindings), allowing users to switch between high-performance/speed and high-flexibility modes. The C++ core reimplements the sparse SLAM initially implemented in Python, exposing core SLAM classes (frames, keyframes, map points, maps, cameras, optimizers, tracking, and local mapping) to Python via pybind11.

The C++ implementation follows a streamlined design where all core data resides in C++, with Python serving as an interface layer. C++ classes mirror their Python counterparts, maintaining identical interfaces and data field names. The bindings support zero-copy data exchange (e.g., descriptors) and safe memory ownership across the Python/C++ boundary, leveraging automatic zero-copy sharing of NumPy array memory with C++ when possible.

To enable the C++ sparse-SLAM core, set `USE_CPP_CORE = True` in `pyslam/config_parameters.py`. The module is currently **under active development**.

The codebase is organized into the following categories:

- **Core SLAM Classes**: Main C++ implementations (`frame.cpp/h`, `keyframe.cpp/h`, `map_point.cpp/h`, `map.cpp/h`, `camera.cpp/h`, `camera_pose.cpp/h`, `optimizer_g2o.cpp/h`, `tracking_core.cpp/h`, `local_mapping_core.cpp/h`)
- **Serialization**: JSON and NumPy serialization modules for data persistence and Python interop
- **Python Bindings**: pybind11 module definitions that expose C++ classes to Python
- **Type Casters**: pybind11 type casters for custom type conversions (OpenCV, Eigen, JSON, dictionary types)
- **Utilities**: Helper functions for geometry, features, descriptors, image processing, NumPy/Eigen operations, and serialization
- **Tests**: C++ unit tests and Python integration tests

The C++ core adopts a streamlined design philosophy:

- **All core data resides in C++**: Python serves purely as an interface layer
- **Direct pybind11 exposure**: Python objects are lightweight views of underlying C++ objects
- **Automatic zero-copy**: pybind11 automatically shares NumPy array memory with C++ when possible
- **RAII-based ownership**: C++ smart pointers manage object lifetimes safely and efficiently

4.5 Saving and reloading

Save the a map

When you run the script `main_slam.py` (`main_map_dense_reconstruction.py`):

- You can save the current map state by pressing the button `Save` on the GUI. This saves the current map along with front-end, and backend configurations into the default folder `results/slam_state` (`results/slam_state_dense_reconstruction`).
- To change the default saving path, open `config.yaml` and update target `folder_path` in the section:

```
SYSTEM_STATE:
  folder_path: results/slam_state   # default folder path (relative to repository root) where the
                                    # system state is saved or reloaded
```

Reload a saved map and relocalize in it

- A saved map can be loaded and visualized in the GUI by running:

```
$ . pyenv-activate.sh   #  Activate pyslam python virtual environment. This is only needed once in a new terminal.
$ ./main_map_viewer.py  #  Use the --path options to change the input path
```

- To enable map reloading and relocalization when running `main_slam.py`, open `config.yaml` and set

```
SYSTEM_STATE:
  load_state: True                # flag to enable SLAM state reloading (map state + loop closing state)
  folder_path: results/slam_state # default folder path (relative to repository root) where the
                                  # system state is saved or reloaded
```

Note that pressing the `Save` button saves the current map, front-end, and backend configurations. Reloading a saved map replaces the current system configurations to ensure descriptor compatibility.

Trajectory saving

Estimated trajectories can be saved in three formats: *TUM* (The Open Mapping format), *KITTI* (KITTI Odometry format), and *EuRoC* (EuRoC MAV format). pySLAM saves two **types** of trajectory estimates:

- **Online**: In *online* trajectories, each pose estimate depends only on past poses. A pose estimate is saved at the end of each front-end iteration for the current frame.
- **Final**: In *final* trajectories, each pose estimate depends on both past and future poses. A pose estimate is refined multiple times by LBA windows that include it, as well as by PGO and GBA during loop closures.

To enable trajectory saving, open `config.yaml` and search for the `SAVE_TRAJECTORY`: set `save_trajectory: True`, select your `format_type` (`tum`, `kitti`, `euroc`), and the output filename. For instance for a `tum` format output:

```
SAVE_TRAJECTORY:
  save_trajectory: True
  format_type: kitti            # supported formats: `tum`, `kitti`, `euroc`
  output_folder: results/metrics # relative to pyslam root folder
  basename: trajectory          # basename of the trajectory saving output
```

Optimization engines

Currently, pySLAM supports both `g2o` and `gtsam` for graph optimization, with `g2o` set as the default engine. You can enable `gtsam` by setting to `True` the following parameters in `config_parameters.py`:

```
    # Optimization engine
    kOptimizationFrontEndUseGtsam = True
    kOptimizationBundleAdjustUseGtsam = True
    kOptimizationLoopClosingUseGtsam = True
```

Additionally, the `gtsam_factors` package provides custom Python bindings for features not available in the original gtsam framework. See here for further details.

4.6 SLAM GUI

Some quick information about the non-trivial GUI buttons of `main_slam.py`:

- `Step`: Enter the *Step by step mode*. Press the button `Step` a first time to pause. Then, press it again to make the pipeline process a single new frame.
- `Save`: Save the map into the file `map.json`. You can visualize it back by using the script `main_map_viewer.py` (as explained above).
- `Reset`: Reset SLAM system.
- `Draw Ground Truth`: If a ground truth dataset (e.g., KITTI, TUM, EUROC, or REPLICA) is loaded, you can visualize it by pressing this button. The ground truth trajectory will be displayed in 3D and will be progressively aligned with the estimated trajectory, updating approximately every 10-30 frames. As more frames are processed, the alignment between the ground truth and estimated trajectory becomes more accurate. After about 20 frames, if the button is pressed, a window will appear showing the Cartesian alignment errors along the main axes (i.e., e_x, e_y, e_z and the history of the total $RMSE$ between the ground truth and the aligned estimated trajectories.

4.7 Monitor the logs for tracking, local mapping, and loop closing simultaneously

The logs generated by the modules `local_mapping.py`, `loop_closing.py`, `loop_detecting_process.py`, `global_bundle_adjustments.py`, and `volumetric integrator_<X>.py` are collected in the files `local_mapping.log`, `loop_closing.log`, `loop_detecting.log`, `gba.log`, and `volumetric_integrator.log`, which are all stored in the folder `logs`.

For debugging, you can monitor one of the them in parallel by running the following command in a separate shell:

```
$ tail -f logs/<log file name>
```

Otherwise, to check all parallel logs with tmux, run:

```
$ ./scripts/launch_tmux_logs.sh
```

To launch slam and check all logs in a single tmux, run:

```
$ ./scripts/launch_tmux_slam.sh
```

Press `CTRL+A` followed by `CTRL+Q` to exit from `tmux` environment.

4.8 Evaluating SLAM

Run a SLAM evaluation

The `main_slam_evaluation.py` script enables automated SLAM evaluation by executing `main_slam.py` across a collection of *datasets* and configuration *presets*. The main input to the script is an evaluation configuration file (e.g., `evaluation/configs/evaluation.json`) that specifies which datasets and presets to be used. For convenience, sample configurations for the datasets `TUM`, `EUROC` and `KITTI` datasets are already provided in the `evaluation/configs/` directory.

For each evaluation run, results are stored in a dedicated subfolder within the `results` directory, containing all the computed metrics. These metrics are then processed and compared. The final output is a report, available in PDF, LaTeX, and HTML formats, that includes comparison tables summarizing the *Absolute Trajectory Error* (ATE), the maximum deviation from the ground truth trajectory and other metrics.

Evaluation results are presented in the following subsections. For convenience, they are also available at this link. The evaluation uses commit *f7c9a13* with the following presets: `baseline`, `root_sift`, and `superpoint`, which correspond to local feature extractors `ORB2`, `root_SIFT`, and `SuperPoint`, respectively.

TUM Evaluation

Table 1: TUM: Table RMSE

Dataset	baseline	root_sift	superpoint
rgbd_dataset_freiburg1_desk	0.06634	0.05289	0.04815
rgbd_dataset_freiburg1_desk2	0.04645	0.06255	0.03868
rgbd_dataset_freiburg1_room	0.05885	0.07968	0.07199
rgbd_dataset_freiburg1_xyz	0.01196	0.01758	0.01726
rgbd_dataset_freiburg3_long_office_household	0.00921	0.00982	0.00952
rgbd_dataset_freiburg3_nostructure_texture_far	0.08397	0.11342	0.12118
rgbd_dataset_freiburg3_nostructure_texture_near_withloop	0.02245	0.05022	0.05037
Average	0.04275	0.05517	0.05102
Std Dev	0.0362	0.04531	0.04503
Best (Average) Preset	baseline		
Best (Average) Metric	0.04275		

Table 3: TUM: Table Max

Dataset	baseline	root_sift	superpoint
rgbd_dataset_freiburg1_desk	0.326	0.19361	0.22686
rgbd_dataset_freiburg1_desk2	0.44543	0.28865	0.38157
rgbd_dataset_freiburg1_room	0.14959	0.2838	0.17632
rgbd_dataset_freiburg1_xyz	0.06059	0.0677	0.0635
rgbd_dataset_freiburg3_long_office_household	0.03609	0.03543	0.04005
rgbd_dataset_freiburg3_nostructure_texture_far	0.29727	0.4361	0.70826
rgbd_dataset_freiburg3_nostructure_texture_near_withloop	0.09011	0.13774	0.11602
Average	0.20073	0.20615	0.24465
Std Dev	0.18661	0.18182	0.26334
Best (Average) Preset	baseline		
Best (Average) Metric	0.20073		

Table 5: TUM: Table Percent Lost

Dataset	baseline	root_sift	superpoint
rgbd_dataset_freiburg1_desk	1.364	1.502	1.674
rgbd_dataset_freiburg1_desk2	0.548	1.55	0.612
rgbd_dataset_freiburg1_room	0.074	0.148	0.088
rgbd_dataset_freiburg1_xyz	0.05	0.076	0.078
rgbd_dataset_freiburg3_long_office_household	0.0	0.0	0.0
rgbd_dataset_freiburg3_nostructure_texture_far	0.622	0.622	0.666
rgbd_dataset_freiburg3_nostructure_texture_near_withloop	0.024	0.036	0.036
Average	0.38314	0.562	0.45057
Std Dev	0.50438	0.82947	0.59847
Best (Average) Preset	baseline		
Best (Average) Metric	0.38314		

EUROC Evaluation

Table 7: EUROC: Table RMSE

Dataset	baseline	root_sift	superpoint
V101	0.08819	0.08816	0.08834
V102	0.06852	0.06609	0.06694
V201	0.07062	0.06409	0.09735
V202	0.62539	0.56925	0.53736
MH01	0.03775	0.03781	0.04172
MH02	0.04217	0.0456	0.04177
MH03	0.0512	0.04905	0.04882
MH04	0.0702	0.05907	0.0646
MH05	0.08177	0.06607	0.07131
Average	0.1262	0.11613	0.11758
Std Dev	0.19831	0.17517	0.15435
Best (Average) Preset	root_sift		
Best (Average) Metric	0.11613		

Table 9: EUROC: Table Max

Dataset	baseline	root_sift	superpoint
V101	0.16335	0.163	0.16208
V102	0.14545	0.12379	0.13136
V201	0.15864	0.18921	0.22163
V202	2.06607	2.52628	1.97847
MH01	0.09141	0.10259	0.21303
MH02	0.11922	0.1318	0.11196
MH03	0.19995	0.17533	0.14082
MH04	0.32021	0.27938	0.26722
MH05	0.24828	0.17474	0.18991
Average	0.39029	0.42957	0.37961
Std Dev	0.67128	0.75543	0.6093
Best (Average) Preset	superpoint		
Best (Average) Metric	0.37961		

Table 11: EUROC: Table Percent Lost

Dataset	baseline	root_sift	superpoint
V101	0.0	0.0	0.0
V102	0.0	0.0	0.0
V201	0.04	0.04	0.04
V202	0.146	0.138	0.112
MH01	0.05	0.074	0.08
MH02	0.018	0.026	0.012
MH03	0.046	0.03	0.032
MH04	0.0	0.01	0.0
MH05	0.07	0.016	0.034
Average	0.04111	0.03711	0.03444
Std Dev	0.05351	0.04829	0.04435
Best (Average) Preset	superpoint		
Best (Average) Metric	0.03444		

KITTI Evaluation

Table 13: KITTI: Table RMSE

Dataset	baseline	root_sift	superpoint
00	3.947	3.24849	3.93432
01	21.60014	21.86468	23.37292
02	6.1194	5.6707	10.14455
03	5.96451	5.92601	5.88895
04	1.74556	1.76121	1.65506
05	2.13915	2.11047	2.52263
06	2.74011	2.73981	2.6784
07	1.12358	1.12823	1.09496
08	3.99078	4.13702	4.14543
09	4.26068	4.35988	4.06244
10	2.22097	2.25127	2.27694
Average	5.07744	5.01798	5.61605
Std Dev	5.47265	5.63609	6.77
Best (Average) Preset	root_sift		
Best (Average) Metric	5.01798		

Table 15: KITTI: Table Max

Dataset	baseline	root_sift	superpoint
00	6.82983	5.8663	7.04067
01	33.32903	33.85867	36.62253
02	13.97623	9.47974	21.05188
03	10.16642	10.16978	10.06014
04	3.09135	3.0576	2.87271
05	3.81484	3.77687	4.9547
06	6.53758	5.14239	5.11673
07	1.84418	1.82355	1.8655
08	10.809	11.23635	10.75959
09	8.53888	8.70237	8.31166
10	4.13901	4.37849	4.27905
Average	9.37058	8.86292	10.26683
Std Dev	8.62548	8.62145	12.23529
Best (Average) Preset	root_sift		
Best (Average) Metric	8.86292		

Table 17: KITTI: Table Percent Lost

Dataset	baseline	root_sift	superpoint
00	0.0	0.038	0.012
01	0.0	0.0	0.0
02	0.012	0.004	0.004
03	0.0	0.0	0.0
04	0.0	0.0	0.0
05	0.0	0.0	0.028
06	0.108	0.018	0.0
07	0.0	0.0	0.0
08	0.0	0.0	0.0
09	0.0	0.0	0.0
10	0.0	0.0	0.0
Average	0.01091	0.00545	0.004
Std Dev	0.07244	0.02373	0.0196
Best (Average) Preset	superpoint		
Best (Average) Metric	0.004		

pySLAM performances and comparative evaluations

For a comparative evaluation of the "*online*" trajectory estimated by pySLAM versus the "*final*" trajectory estimated by ORB-SLAM3, check out this nice notebook. For more details about "online" and "final" trajectories, refer to Section 4.5.

Note: Unlike ORB-SLAM3, which only saves the final pose estimates (recorded after the entire dataset has been processed), pySLAM saves both online and final pose estimates. For details on how to save trajectories in pySLAM, refer to this section. When you click the `Draw Ground Truth` button in the GUI (see here), you can visualize the *Absolute Trajectory Error* (ATE or *RMSE*) history and evaluate both online and final errors up to the current time.

4.9 Scene from Views

The *Scene from Views* module provides a unified interface for 3D scene reconstruction from multiple views. It follows a modular architecture that allows easy integration of different reconstruction models while maintaining a consistent API.

The module is built around a factory pattern with a base class `SceneFromViewsBase` that implements a unified three-step reconstruction pipeline:

1. `preprocess_images()`: Preprocesses input images for the specific model
2. `infer()`: Runs model inference on preprocessed images
3. `postprocess_results()`: Converts raw model output to standardized `SceneFromViewsResult`

The `SceneFromViewsResult` structure standardizes the output format across all models, containing:

- `global_point_cloud`: Merged point cloud in world coordinates
- `global_mesh`: Merged mesh in world coordinates
- `camera_poses`: List of camera-to-world transformation matrices (4x4)
- `processed_images`: List of processed images used by the model
- `depth_predictions`: List of depth maps if available
- `point_clouds`: List of per-view point clouds
- `intrinsics`: List of camera intrinsic matrices if available
- `confidences`: List of confidence maps if available

The following reconstruction models are currently supported:

- `DUST3R`: Dense 3D reconstruction from arbitrary image collections without requiring known camera intrinsics or poses. Predicts dense 3D pointmaps for image pairs, from which depth maps and camera parameters can be recovered. Supports global alignment optimization to merge pairwise reconstructions.

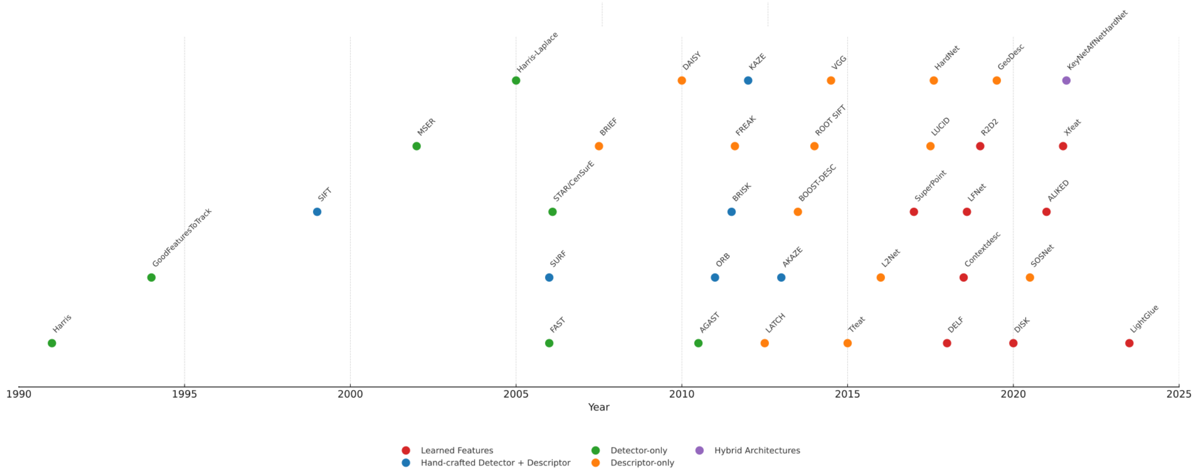


Figure 10: Timeline of some of the most famous local features for image matching, place recognition and SLAM.

- `MAST3R`: Builds on DUSt3R by adding a 3D-aware dense matching head. Produces both dense 3D pointmaps and dense local features for highly accurate matching, with sparse global alignment and optional TSDF-based fusion.
- `DEPTH_ANYTHING_V3`: Monocular depth estimation model that can produce both relative and metric depth. Supports optional camera pose and intrinsic parameter estimation for reconstruction pipelines.
- `MVDUST3R`: Multi-view variant of DUSt3R that processes multiple unposed RGB views in a single feed-forward pass, using multi-view decoder blocks to jointly reason about all input views.
- `VGGT`: Large feed-forward transformer for 3D reconstruction that directly predicts camera parameters, pointmaps, depth maps, and 3D point tracks from one or many input views in a single forward pass.
- `VGGT_ROBUST`: VGGT variant mirroring the `robust_vggt` demo. It scores each view against an anchor frame using global attention maps and cosine similarity, rejects low-scoring views before the final forward pass, and returns metadata about dropped/kept views (`rejected_indices`, `survivor_indices`). Configurable knobs include anchor weighting (`attn_a`, `cos_a`), rejection threshold (`rej_thresh`), anchor choice (`use_most_central_as_reference`), and masking/confidence filters. Default checkpoint: `facebook/VGGT-1B`.

The module supports both pairwise models (DUSt3R, MASt3R) that process image pairs and perform global alignment, as well as multi-view models (MV-DUSt3R, VGGT) that process multiple views simultaneously. Usage examples are available in the script `main_scene_from_views.py`.

5 Supported components and models

5.1 Supported local features

Fig. 10 shows a timeline with some of the most famous local features for image matching, place recognition and SLAM. At present time, pySLAM supports the following feature **detectors**:

- FAST [54]
- Good features to track [57]
- ORB [55]
- ORB2 (improvements of ORB-SLAM2 to ORB detector)
- SIFT [31]
- SURF [8]
- KAZE [1]
- AKAZE [2]
- BRISK [24]
- AGAST

- MSER [36]
- StarDector/CenSurE
- Harris-Laplace
- SuperPoint
- D2-Net [16]
- DELF [47]
- Contextdesc [34]
- LFNet [48]
- R2D2 [52]
- Key.Net [5]
- DISK [67]
- ALIKED [6]
- Xfeat [7]
- KeyNetAffNetHardNet (KeyNet detector + AffNet + HardNet descriptor)

The following feature **descriptors** are supported:

- ORB [55]
- SIFT [31]
- ROOT SIFT
- SURF [8]
- AKAZE [2]
- BRISK [24]
- FREAK
- SuperPoint
- Tfeat
- BOOST-DESC [66]
- DAISY [65]
- LATCH [25]
- LUCID
- VGG [58]
- Hardnet [39]
- GeoDesc [70]
- SOSNet
- L2Net
- Log-polar descriptor
- D2-Net [16]
- DELF [47]
- Contextdesc [34]
- LFNet [48]
- R2D2 [52]
- BEBLID
- DISK [67]
- ALIKED [6]

- Xfeat [7]
- KeyNetAffNetHardNet (KeyNet detector + AffNet + HardNet descriptor)

For more information, refer to pyslam/local_features/feature_types.py file. Some of the local features consist of a *joint detector-descriptor*. You can start playing with the supported local features by taking a look at `test/cv/test_feature_manager.py` and `main_feature_matching.py`.

In both the scripts `main_vo.py` and `main_slam.py`, you can create your preferred detector-descritor configuration and feed it to the function `feature_tracker_factory()`. Some ready-to-use configurations are already available in the file pyslam/local_features/feature_tracker_configs.py

The function `feature_tracker_factory()` can be found in the file `pyslam/local_features/feature_tracker.py`. Take a look at the file `pyslam/local_features/feature_manager.py` for further details.

N.B.: You just need a *single* python environment to be able to work with all the supported local features!

5.2 Supported matchers

- `BF`: Brute force matcher on descriptors (with KNN).
- FLANN [42]
- XFeat [7]
- LightGlue
- LoFTR

See the file `pyslam/local_features/feature_matcher.py` for further details.

5.3 Supported global descriptors and local descriptor aggregation methods

Local descriptor aggregation methods

- Bag of Words (BoW): DBoW2 [19], DBoW3. [paper]
- Vector of Locally Aggregated Descriptors: VLAD [3]. [paper]
- Incremental Bags of Binary Words (iBoW) via Online Binary Image Index: iBoW, OBIndex2. [paper]
- Hyperdimensional Computing: HDC [44]. [paper]

NOTE: *iBoW* and *OBIndex2* incrementally build a binary image index and do not need a prebuilt vocabulary. In the implemented classes, when needed, the input non-binary local descriptors are transparently transformed into binary descriptors.

Global descriptors

Also referred to as *holistic descriptors*:

- SAD
- AlexNet
- NetVLAD [3]
- HDC-DELF
- CosPlace [10]
- EigenPlaces [11]
- MegaLoc [9]

Different loop closing methods are available. These combines the above aggregation methods and global descriptors. See the file pyslam/loop_closing/loop_detector_configs.py for further details.

5.4 Supported depth prediction models

Both monocular and stereo depth prediction models are available. SGBM algorithm has been included as a classic reference approach.

- SGBM: Depth SGBM from OpenCV (Stereo, classic approach) [20]
- Depth-Pro (Monocular) [12]
- DepthAnythingV2 (Monocular) [61]
- RAFT-Stereo (Stereo) [62]
- CREStereo (Stereo) [27]

- MASt3R (Monocular/Stereo) [23]
- MV-DUSt3R (Monocular/Stereo) [60]

5.5 Supported volumetric mapping methods

- A C++ template-based voxel grid implementation leverages parallel spatial hashing, supporting both direct voxel hashing and indirect voxel-block hashing strategies. Parallel execution is managed using TBB, and the design accommodates both simple and semantic voxels. Further information about the volumetric grid models is available here.
- TSDF with voxel block grid (parallel spatial hashing) [15]
- Incremental 3D Gaussian Splatting. See here and MonoGS for a description of its backend [37, 21].

5.6 Supported semantic segmentation methods

- DeepLabv3 [13]: from `torchvision`, pre-trained on COCO/VOC.
- Segformer [71]: from `transformers`, pre-trained on Cityscapes or ADE20k.
- CLIP [28]: from `f3rm` package for open-vocabulary support.
- EOV_SEG [45]: EOV-Seg: Efficient Open-Vocabulary Panoptic Segmentation.
- DETIC [74]: Detecting Twenty-thousand Classes using Image-level Supervision.
- ODISE [72]: Open-Vocabulary Panoptic Segmentation with Text-to-Image Diffusion Models.

5.7 Configuration

Main configuration file

Refer to this section for how to update the main configuration file config.yaml and affect the configuration parameters in config_parameters.py.

Datasets

The following datasets are supported:

Dataset	type in `config.yaml`
KITTI odometry data set (grayscale, 22 GB)	`type: KITTI_DATASET`
TUM dataset	`type: TUM_DATASET`
ICL-NUIM dataset	`type: ICL_NUIM_DATASET`
EUROC dataset	`type: EUROC_DATASET`
REPLICA dataset	`type: REPLICA_DATASET`
TARTANAIR dataset	`type: TARTANAIR_DATASET`
ScanNet dataset	`type: SCANNET_DATASET`
ROS1 bags	`type: ROS1BAG_DATASET`
ROS2 bags	`type: ROS2BAG_DATASET`
MCAP file	`type: MCAP_DATASET`
Video file	`type: VIDEO_DATASET`
Folder of images	`type: FOLDER_DATASET`

Use the download scripts available in the folder `scripts` to download some of the following datasets.

KITTI Datasets

pySLAM code expects the following structure in the specified KITTI path folder (specified in the section `KITTI_DATASET` of the file `config.yaml`). :

```
+-- sequences
|   +-- 00
|   ...
|   +-- 21
+-- poses
    +-- 00.txt
    ...
    +-- 10.txt
```

1. Download the dataset (grayscale images) from http://www.cvlibs.net/datasets/kitti/eval_odometry.php and prepare the KITTI folder as specified above
2. Select the corresponding calibration settings file (section `KITTI_DATASET: settings:` in the file `config.yaml`)

TUM Datasets

pySLAM code expects a file `associations.txt` in each TUM dataset folder (specified in the section `TUM_DATASET:` of the file `config.yaml`).

1. Download a sequence from vision.in.tum.de/data/datasets/rgbd-dataset/download and uncompress it.
2. Associate RGB images and depth images using the python script associate.py. You can generate your `associations.txt` file by executing:
   ```
   $ python associate.py PATH_TO_SEQUENCE/rgb.txt PATH_TO_SEQUENCE/depth.txt > associations.txt
   # pay attention to the order!
   ```
3. Select the corresponding calibration settings file (section `TUM_DATASET: settings:` in the file `config.yaml`).

ICL-NUIM Datasets

Follow the same instructions provided for the TUM datasets.

EuRoC Datasets

1. Download a sequence (ASL format) from http://projects.asl.ethz.ch/datasets/doku.php?id=kmavvisualinertialdatasets (check this direct link)
2. Use the script `io/generate_euroc_groundtruths_as_tum.sh` to generate the TUM-like groundtruth files `path + '/' + name + '/mav0/state_groundtruth_estimate0/data.tum'` that are required by the `EurocGroundTruth` class.
3. Select the corresponding calibration settings file (section `EUROC_DATASET: settings:` in the file `config.yaml`).

Replica Datasets

1. You can download the zip file containing all the sequences by running:
   ```
   $ wget https://cvg-data.inf.ethz.ch/nice-slam/data/Replica.zip
   ```
2. Then, uncompress it and deploy the files as you wish.
3. Select the corresponding calibration settings file (section `REPLICA_DATASET: settings:` in the file `config.yaml`).

Tartanair Datasets

1. You can download the datasets from https://theairlab.org/tartanair-dataset
2. Then, uncompress them and deploy the files as you wish.
3. Select the corresponding calibration settings file (section `TARTANAIR_DATASET: settings:` in the file `config.yaml`).

ScanNet Datasets

1. You can download the datasets following instructions in http://www.scan-net.org. You will need to request the dataset from the authors.
2. There are two versions you can download:
   - A subset of pre-processed data termed as `tasks/scannet_frames_2k`: this version is smaller, and more generally available for training neural networks. However, it only includes one frame out of each 100, which makes it unusable for SLAM. The labels are processed by mapping them from the original Scannet label annotations to NYU40.
   - The raw data: this version is the one used for SLAM. You can download the whole dataset (TBs of data) or specific scenes. A common approach for evaluation of semantic mapping is to use the `scannetv2_val.txt` scenes. For downloading and processing the data, you can use the following repository as the original Scannet repository is tested under Python 2.7 and does't support batch downloading of scenes.
3. Once you have the `color`, `depth`, `pose`, and (optional for semantic mapping) `label` folders, you should place them following `{path_to_scannet}/scans/{scene_name}/[color, depth, pose, label]`. Then, configure the `base_path` and `name` in the file `config.yaml`.

4. Select the corresponding calibration settings file (section `SCANNET_DATASET: settings:` in the file `config.yaml`). NOTE: the RGB images are rescaled to match the depth image. The current intrinsic parametes in the existing calibration file reflect that.

ROS1 bags

1. Source the main ROS1 `setup.bash` after you have sourced the `pyslam` python environment.
2. Set the paths and `ROS1BAG_DATASET: ros_parameters` in the file `config.yaml`.
3. Select/prepare the correspoding calibration settings file (section `ROS1BAG_DATASET: settings:` in the file `config.yaml`). See the available yaml files in the folder `Settings` as an example.

ROS2 bags

1. Source the main ROS2 `setup.bash` after you have sourced the `pyslam` python environment.
2. Set the paths and `ROS2BAG_DATASET: ros_parameters` in the file `config.yaml`.
3. Select/prepare the correspoding calibration settings file (section `ROS2BAG_DATASET: settings:` in the file `config.yaml`). See the available yaml files in the folder `Settings` as an example.

MCAP file

A concise introduction of the MCAP format is available at https://foxglove.dev/blog/introducing-the-mcap-file-format. These files can be also recorded and played back by using ROS2 tools.

Video and Folder Datasets

You can use the `VIDEO_DATASET` and `FOLDER_DATASET` types to read generic video files and image folders (specifying a glob pattern), respectively. A companion ground truth file can be set in the simple format type: Refer to the class `SimpleGroundTruth` in `io/ground_truth.py` and check the script `io/convert_groundtruth_to_simple.py`.

5.8 Camera Settings

The folder `settings` contains the camera settings files which can be used for testing the code. These are the same used in the framework ORB-SLAM2 [43]. You can easily modify one of those files for creating your own new calibration file (for your new datasets).

In order to calibrate your camera, you can use the scripts in the folder `calibration`. In particular: 1. Use the script `grab_chessboard_images.py` to collect a sequence of images where the chessboard can be detected (set the chessboard size therein, you can use the calibration pattern `calib_pattern.pdf` in the same folder) 2. Use the script `calibrate.py` to process the collected images and compute the calibration parameters (set the chessboard size therein)

For more information on the calibration process, see this tutorial [35] or this other link [50].

If you want to **use your camera**, you have to:

- Calibrate it and configure settings/WEBCAM.yaml accordingly.
- Record a video (for instance, by using `save_video.py` in the folder `calibration`).
- Configure the `VIDEO_DATASET` section of `config.yaml` in order to point to your recorded video.

6 Credits

The following is a list of frameworks that inspired or has been integrated into pySLAM. Many thanks to their Authors for their great work.

- Pangolin
- g2opy
- ORBSLAM2 [43]
- SuperPointPretrainedNetwork [14]
- Tfeat [4]
- Image Matching Benchmark Baselines [69]
- Hardnet [40]
- GeoDesc [33]
- SOSNet [64]
- L2Net [63]
- Log-polar descriptor [18]

- D2-Net [17]
- DELF [46]
- Contextdesc [32]
- LFNet [49]
- R2D2 [53]
- BEBLID [59]
- DISK [68]
- Xfeat [51]
- LightGlue [29]
- Key.Net [5]
- Twitchslam
- MonoVO
- VPR_Tutorial [56]
- DepthAnythingV2 [73]
- DepthPro [12]
- RAFT-Stereo [30]
- CREStereo and CREStereo-Pytorch [26]
- MonoGS [38]
- MASt3R [23]
- MV-DUSt3R [60]
- Many thanks to Anathonic for adding the first version of the trajectory-saving feature and for the comparison notebook: pySLAM vs ORB-SLAM3.
- Many thanks to David Morilla Cabello for his great work on creating the first version of sparse semantic mapping module in pySLAM [41].

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