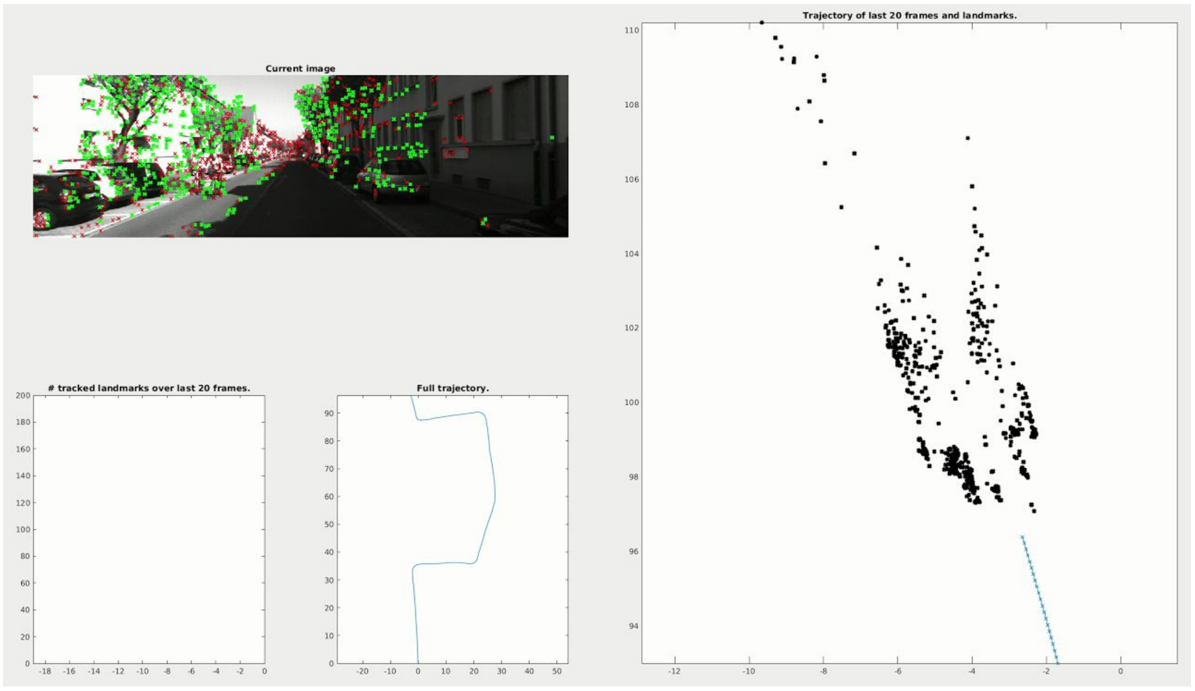
Mini project: A Visual Odometry pipeline!

This document describes the goal of the mini-project, the expected result, and gives you a number of guidelines regarding what to do and where to start.

1 Preliminaries


Current image
# tracked landmarks over last 20 frames.
Full trajectory.
Trajectory of last 20 frames and landmarks.

A Youtube playlist with our progress on the reference implementation can be found at https://www.youtube.com/playlist?list=PLI5XgAFFHqZiAg6yd0XKOTRgkCE4QTm54 .

1.1 Goal of the project

The goal of this mini-project is to implement a simple, monocular, visual odometry (VO) pipeline with the most essential features: initialization of 3D landmarks, keypoint tracking between two frames, pose estimation using established 2D $\leftrightarrow$ 3D correspondences, and triangulation of new landmarks.

You will use the knowledge acquired during the class, and specifically the different modules developed during the exercise sessions.

1.2 Datasets

You are provided with three datasets to test your pipeline:

- The parking dataset (monocular)
- The KITTI dataset (stereo)
- The Malaga dataset (stereo)

1.3 Grading

You will be graded according to three things:

1) The quality of the pose estimation from your VO pipeline.
2) The text report that you will have to hand in.
3) Whether you implemented one or multiple bonus features, or did something in addition to the basic requirements (and explained it in the report). A (non-exhaustive) list of ideas is given later.

1) We will **not** do a strict quantitative evaluation of the quality of your VO pipelines. Instead, we will run your code on several datasets, and judge it from a qualitative point of view, paying particular attention to the following points (sorted by decreasing order of importance):

- The features you implemented. A 6 can only be achieved with a completely monocular pipeline. If your pipeline requires stereo frames in continuous operation, your grade will be ≤ 4.5. If your pipeline requires stereo frames for initialization only, your grade will be ≤ 5. Note that no penalty is given if a bonus feature (see below) requires stereo frames.
- How far does the pipeline go without failing or deviating significantly from the ground truth. Note that with the KITTI and Malaga sequences, scale drift will be difficult to avoid, we will take that into account when judging your VO pipelines).
- How fast does your code run (in particular for Matlab code, we will check whether you paid attention to using vectorized operations instead of for loops whenever possible).

2) and 3): The project report should summarize the work that you did and specify exactly what your VO pipeline does. For example, whether it is monocular or stereo, and how well it performs on the provided datasets (with plots). The project report is also the place to describe the (eventual) bonus features that you implemented, or the additional work you did that over the basic VO pipeline required, and how this impacts the quality of your VO pipeline. Note that having implemented an additional feature which degrades the quality of your VO pipeline will be accepted and valued as long as i) the implemented feature is properly motivated and described, and ii) an analysis showing the effect of your additional feature is provided in the report. You should also upload or attach a video of your working pipeline.

(Non-exhaustive) list of bonus features/improvements (order by increasing weight in terms of bonus points)

- **Any idea that you come up with and think will improve the quality of your VO pipeline (you may write an email to us for confirmation).**

- Refine the estimated pose (after P3P) by minimizing the reprojection error in a nonlinear fashion. This will be more clear after lecture 13 about Bundle Adjustment.
- Record your own dataset - with your smartphone's camera (that you will have calibrated beforehand using the Matlab toolbox).
- Propose and implement improvements to combat scale drift (without using stereo frames).
- Detailed, quantitative analyses that compare several approaches that can be applied to the same component of the VO.
- Structure-Only Bundle Adjustment (i.e. refinement of landmark positions).
- Full Bundle Adjustment (motion and structure) on a selected set of recent frames (keyframes), to improve the current estimate.
- Loop detection using a Bag of Words approach (see the upcoming lecture 12 and exercise 9) + include the loop closure constraints in your Bundle Adjustment step.

1.4 Code building blocks and use of external libraries

You can of course use the modules that you built during the exercise sessions. However, we would highly recommend you to use the implementation provided to you to limit the potential amount of bugs. For your convenience, you will find packaged in the provided archive the code from all the previous classes.

External libraries

Although we encourage you to use the modules that have been developed during the exercises sessions, you are allowed to use external functions (for example, functions from Matlab or OpenCV) for everything that has been covered during the exercises. For example, for estimating the fundamental matrix, you can either use the function *fundamentalEightPoint_normalized* developed during the exercises, or the function *estimateFundamentalMatrix* from Matlab's Computer Vision System Toolbox.

We won't provide help with using external functions or libraries.

Note that we will ask you detailed questions about the theory of the separate modules during the oral exam, so implementing them (as was done during the exercises) is a good idea to prepare optimally for the exams.

1.5 Hand-out

Code

- **Matlab**

You should provide A ZIP archive containing a **main.m** file which we can run directly without any change in the code. Please also indicate which version of Matlab you are using in case of incompatibilities.

Note that we will set the variables corresponding to the dataset paths (e.g. **parking_path**, **kitti_path**, **malaga_path** prior to running your code.

- **Other languages**

You are allowed to use any language of your choice (for example Python, C++, etc.). However, it is your responsibility to ensure that we can run your code with minimal effort, on Ubuntu 14.04 (with Python 2.7 and gcc 4.9.2). As mentioned above, you are allowed to use external dependencies (such as OpenCV for example) provided that the functions you use have been implemented in the exercises.

In any case, you must:

- Provide detailed explanations regarding how to run your code (provide a Makefile for C/C++ for example, list the necessary dependencies and how to install them).
- Make sure that the necessary dependencies are easy to install (e.g. we can just use *sudo apt-get install [lib]*).

Report and Video

The content of the report has been detailed above. Note that the **maximum number of pages allowed for the report is 5 pages** (excluding plots, images and installation/run instructions). If you have a working pipeline, you should also upload or attach a video of it.

2 Overview of the proposed pipeline

We first give a global overview of the proposed pipeline and the different components involved. We will then go into more details separately into each component.

Notations

Throughout the next section, we will use the following notations:

- We denote the set of all N frames in a dataset by: $\{I^i \equiv I(t^i)\}_{i=1..N}$,
- We denote the pose of the camera at time t^i by ${T^i}_{WC}$.

Overview

The proposed pipeline is composed of two main components:

- An initialization module that extracts an initial set of 2D $\leftrightarrow$ 3D correspondences from the first frames of the sequence.
- A continuous VO module that processes each frame I^i, estimates the current pose of the camera $T^i{}_{WC}$ (using an existing set of landmarks), and regularly triangulates new landmarks.

These two modules can be developed independently from one another, although to test the continuous VO module, you will need to have a working initialization module (see next section "Initialization"; for KITTI, you may use the 2D $\leftrightarrow$ 3D correspondences provided in the RANSAC exercise).

3 Initialization

The continuous VO pipeline described below requires, for initialization, a set of keypoint $\leftrightarrow$ landmarks (i.e. 2D $\leftrightarrow$ 3D) correspondences.
We propose two different ways to extract such an initial set of correspondences: the first uses a stereo pair of images to triangulate landmarks, while the second uses two-view geometry.

We suggest you to proceed as follows:

- Implement the first initialization approach (which is easier to implement; or use the data given for KITTI in the RANSAC exercise).
- Implement the continuous VO pipeline (described in the next section).
- Test it (with the first initialization approach, you need a stereo dataset, e.g. either the KITTI or the Malaga dataset).
- Once the continuous pipeline works correctly, implement the second initialization approach, which is more general and works for monocular VO as well.

3.1 Initialization from a stereo pair of images

Although your VO pipeline will be monocular, i.e. using only the left frames of the sequence $\{I_{left}{}^i\}$, we propose, as a first approach, to use the first stereo pair of frames $\{I_{left}{}^0, I_{right}{}^0\}$ to initialize a set of 3D landmarks. Here is how you can proceed:

- Extract a set of keypoints $\{p_{k,left}\}_{k=1..K}$ in $I_{left}{}^0$ (hint: exercise 3).
- Establish the correspondences $\{p_{k,left} \leftrightarrow p_{k,right}\}$ in $I_{right}{}^0$ using stereo matching (hint: exercise 4).
- Triangulate the keypoint correspondences $\{p_{k,left} \leftrightarrow p_{k,right}\}$ to get an initial set of 3D landmarks $\{X_k{}^0\}$ (see exercise 4).

You can now Initialize the continuous VO pipeline with the newly established set of keypoint $\leftrightarrow$ landmark correspondences $\{p_{k,left} \leftrightarrow X_k{}^0\}$.

3.2 Initialization using two-view geometry, for monocular VO

As you learnt in lecture 6, an alternative way to proceed is to use two-view geometry to estimate the relative pose between two (sufficiently distant) frames, and triangulate a point cloud of landmarks.
You can proceed as follows:

- Manually select two frames I^{i_0} and I^{i_1} at the beginning of the dataset.
- Establish keypoint correspondences between these two frames (hint: exercise 3).
- Estimate the relative pose between the frames and triangulate a point cloud of 3D landmarks (hint: exercise 5). Since the keypoint correspondences from the previous step will inevitably contain some outliers, you will need to use RANSAC (some hints are given below) to filter them out.
- Initialize the continuous VO pipeline with the inlier keypoints and their associated landmarks.

Implementation hints:

- Make sure that the baseline between the two initialization frames is large (i.e. it is better not to use two adjacent frames). Don't pick too distant frames either, otherwise it becomes more difficult to establish keypoint correspondence. For the KITTI dataset, we obtained good results using frame 1 and frame 3 ($i_0 = 1$ and $i_1 = 3$).
- Eight-point algorithm with RANSAC**:** you have seen how to implement robust model estimation with RANSAC in exercise 6. A key ingredient of RANSAC is a way to decide whether a given sample should be considered an inlier, given a model. In the case of RANSAC for fundamental matrix estimation, you can use the epipolar line distance (see lecture 8, page 35) to discriminate inliers from outliers. Specifically, for a given candidate fundamental matrix F, a point correspondence should be considered an inlier if the epipolar line distance is less than a threshold (a threshold of 1 px should give good results).
- Implementing the eight-point algorithm with RANSAC can be quite tricky, so make sure you do proper testing before plugging your initialization code into the continuous VO pipeline. One way you can do this is extend exercise 5 to work with RANSAC. To test it, you may add artificial outliers to the supplied inlier keypoint correspondences.

4 Continuous operation

The continuous VO pipeline is the core component of the proposed VO implementation. Its responsibilities are three-fold:

1) Update the set of keypoints $\leftrightarrow$ landmarks correspondences across frames.
2) Estimate the current camera pose based on an incoming frame and the current set of keypoints $\leftrightarrow$ landmarks (2D $\leftrightarrow$ 3D) correspondences.

3) Regularly triangulate new landmarks for use in the subsequent frames.

Step 1) can be carried out by propagating the 2D ↔ 3D correspondences across keyframes through keypoint tracking between successive frames.
Step 2) can be achieved using PnP (see lecture 3).
Step 3) can be done by maintaining **keypoint tracks**, i.e. sequences of keypoints that are matched in multiple subsequent frames, but which do not yet have an associated 3D landmark. These tracks can be later used to triangulate a new 3D landmarks as soon as this can be done reliably enough.

Steps 1) and 2) are sufficient to make a VO pipeline with basic functionality (i.e. which will use the landmarks triangulated in the initialization phase only), while step 3) is needed for doing VO on a larger scale. For this reason, we suggest to implement first steps 1) and 2), test them on the beginning of the datasets, and then implement step 3).

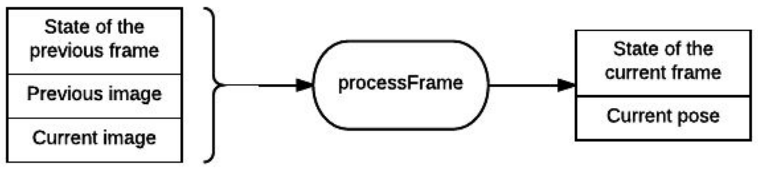
4.1 Steps 1) and 2)

To start with, let us introduce the following notations:

- We denote the set of frames in a dataset by: $\{I^i = I(t^i)\}_{i=1..N}$,
- the set of 2D keypoints (that have an associated landmark) at time t_i by $\{p^i{}_k\}_{k=1..K}$,
- and the set of associated 3D landmarks by $\{X^i{}_k\}_{k=1..K}$.

Additionally, let us denote the pose of the camera at time t^i by $T^i{}_{WC}$.

To perform steps 1) and 2) for every incoming frame, we propose to implement a single function *processFrame* which will be called for every frame in the dataset, with the following inputs and outputs:



where the state of a frame at time t_i, S^i, contains the following data:

- A set of 2D keypoints $\{p^i{}_k\}_{k=1..K}$ (each one of them is associated to a 3D landmark).
- The associated set of 3D landmarks $\{X^i{}_k\}_{k=1..K}$.

Said otherwise, the function *processFrame* has the following form:

$$[S^i, T^i{}_{WC}] = processFrame(I^i, I^{i-1}, S^{i-1})$$

The key idea in this design is that the function inputs solely depend on the output of the previous function call (and the new frame to process), i.e. it has the Markov property. That means we don't need to build a data structure to maintain the history of the past frames, all that is needed is contained in the current state.

As discussed before, *processFrame* should do two things:

1) Propagate the keypoint $\leftrightarrow$ landmark correspondences from I^{i-1} to I^i , i.e. propagate the state S^{i-1} to S^i.
2) Estimate the current camera pose $T^i{}_{WC}$ based on the new state S^i.

We now give further indications for each step.

1) State propagation

To propagate the 2D $\leftrightarrow$ 3D associations $p^{i-1}{}_k \leftrightarrow X^{i-1}{}_k$ (that were established in I^{i-1}) to the next frame I^i, we first establish correspondences $p^{i-1}{}_k \leftrightarrow p_k^i$ by tracking the keypoints $p^{i-1}{}_k$ from frame I^{i-1} to frame I^i. Since the landmarks X_k do not change between frames ($X^i{}_k = X^{i-1}{}_k$), all that is left to do is to update the associations $p_k^i \leftrightarrow X^i{}_k$.

You can proceed as follows:

- For every keypoint $p^{i-1}{}_k \in S^{i-1}$, track that point to the next frame I^i (to obtain $p^i{}_k$):
  - Upon tracking success, update the association $p_k^i \leftrightarrow X^i{}_k$.
  - Upon tracking failure, discard the keypoint p_k and its associated landmark X_k, i.e. do not include them in the updated state S^i.

2) Pose estimation

Use the updated correspondences $p_k^i \leftrightarrow X^i{}_k$ to estimate the pose $T^i{}_{WC}$ using PnP and RANSAC (this has been done exactly in exercise 6).
Implementation tip: In addition to estimating the pose, RANSAC provides you with a list of outlier correspondences. We suggest you to additionally discard these correspondences from the state S^i.

Keypoint tracking between successive keyframes

You have two options to implement keypoint tracking between two successive keyframes:

1) Use the KLT algorithm, that you will learn about in lecture 11 and implement in exercise 8. If you use Matlab. you can use the KLT algorithm implementation from the Computer Vision System Toolbox meanwhile.

2) Use the keypoint description and matching algorithms implemented in exercise 3 . For best results, you may modify the function *matchKeypoints* to search for matches in the next frame only in a small neighborhood of the keypoint in the current frame. This works because frame-to-frame motion is limited. **Implementation hint**: to save computations, you may also store the descriptors associated with each keypoint in the state to reuse them when trying to match keypoints in the next frame.

We recommend using the first option (KLT tracker), since it should be more robust, and it can also provide matches with subpixel-accuracy.

Pose estimation from a set of 2D ↔ 3D correspondences

You have implemented exactly this in exercise 6, using P3P and RANSAC. In this exercise, we had suggested to refine the P3P guess with a DLT solution for all inliers, once the maximum set of inliers has been determined. However, while developing the reference VO, we have found that the DLT solution is very often worse than the P3P guess.

Data storage for the state

Although we said that the state should contain “sets” (i.e. collections of objects), keep in mind that, in Matlab, all the necessary data can be stored as simple 2D matrices (see also implementation tips in the next section).

4.2 Step 3): Triangulating new landmarks

So far, the pipeline can use the landmarks X_k from the initialization phase to localize subsequent frames. However, once the camera has moved far enough, these landmarks might not be visible any more. It is thus necessary to continuously create new landmarks.

We propose an approach which maintains the Markov property of our design and provides new landmarks asynchronously, as soon as they can be triangulated reliably.

The idea is to initialize, for each new frame I, a set of **candidate keypoints (**which of course do not have an associated landmark yet), and try to track them through the next frames. Thus, at every point in time, we maintain a set of candidate keypoints $\{c_m{}^i\}_{m=1..M}$ which have been tracked from previous frames. For every candidate keypoint $c_m{}^i$, we call the sequence

$\Gamma_m = \{c^{i-L_m}{}_m, c^{i-L_m+1}{}_m, ..., c^i{}_m\}$ of tracked keypoints from frame I^{i-L_m} to frame I^i a **keypoint track** (of length L_m).

As soon as a given keypoint track Γ_m meets some conditions (more details on that below), we can reliably triangulate a new landmark from the keypoint observations $\{c^{i-L_m}{}_m, c^{i-L_m+1}{}_m, ..., c^i{}_m\}$, and the camera poses $\{T_{WC}{}^{i-L_m}, T^{i-L_m+1}{}_{WC}, ..., T_{WC}{}^i\}$.

In order to keep the Markov property of the design, we assume that the best triangulation for a given track can be achieved using the most recent observation $c^i{}_m$, the first ever observation of the keypoint $c^{i-L}{}_m$, and the poses $T_{WC}{}^i$ and $T_{WC}{}^{i-L}$.
Hence, all we need to remember for a given keypoint track Γ_m is the first observation $c^{i-L}{}_m$ and the camera pose at the time of the observation $T_{WC}{}^{i-L}$.

We can **add** the following data to the state S^i to reflect this:

- A set of candidate keypoints $\{c_m{}^i\}_{m=1..M}$.
- A set containing the first observations for each keypoint track Γ_m: $\{c_m{}^{i-L_m}\}_{m=1..M}$.
- For each candidate keypoint $c_m{}^i$, the camera pose $T_{WC}{}^i$ at the first observation of the keypoint (see the implementation tips further for suggestions regarding efficient storage of these data).

Again, we do not store the entire keypoint tracks Γ_m, but only the first observation and the associated camera pose.

We now detail the necessary steps to complete step 3).

3) Keypoint track initialization and landmark triangulation

Update the function $processFrame(I^i, I^{i-1}, S^{i-1})$ to perform the following additional steps. after steps 1) and 2):

- Detect new candidate keypoints $\{c_m{}^i\}$ in I^i to initialize new keypoint tracks (see below for hints regarding the number of keypoints to detect).
- For every newly initialized keypoint $c_m{}^i$, remember in the state S^i that this is the first observation of the new keypoint track Γ_m, i.e. store $c^i{}_m$ and $T_{WC}{}^i$ in the state.
- For every candidate keypoint $c_m{}^{i-1} \in S^{i-1}$ (in frame I^{i-1}), try to track it to the current frame:
  - Upon tracking success, update the current state with the tracked keypoint $c_m{}^i$.
  - Upon tracking failure, discard the keypoint track Γ_m.

- Check the triangulability of every candidate keypoint $c_m{}^i$, using the first observation $c_m{}^{i-L_m}$ and the camera pose $T_{WC}{}^{i-L_m}$ stored in the state (see below for hints regarding the triangulability check)
    - If it is possible, triangulate a new landmark X^i using $c_m{}^i$, $c_m{}^{i-L_m}$, $T_{WC}{}^i$ and $T_{WC}{}^{i-L_m}$. Update the state as follows: i) add the newly established correspondence $c_m{}^i \leftrightarrow X^i$ to the state (i.e. update the list of keypoints $\{p^i{}_k\}$ and landmarks $\{X^i{}_k\}$, ii) discard the keypoint track Γ_m.
    - If triangulation is not possible yet, do nothing.

Implementation hints

Data storage

- although in the description we separated the current keypoints into two sets (the ones that have an associated landmark, and the candidate keypoints that are waiting to be triangulated), you may consider using a single 2D matrix (of length $K+M$ where K is the current number of keypoints with landmarks, and M the number of current candidate keypoints) to store all the keypoints jointly. In this case, you can store the current landmarks as a 3D matrix of length $K+M$ and mark with NaN values the entries corresponding to keypoints that do not have an associated landmark yet (e.g. the i-th column of the landmark matrix contains a NaN value if the i-th keypoint does not have an associated landmark). This implementation has the advantage that it avoid copying or moving data around too much.

- to store the first observation of every candidate keypoint $c_m{}^i$, you have multiple options:
    - Record directly $c_m{}^{i-L_m}$ and $T_{WC}{}^{i-L_m}$ in the state. To store the latter with a single matrix, you can reshape the 4×4 transformation matrix $T_{WC}{}^{i-L_m}$ to a 16×1 vector and store all the transformation matrices in a $M \times 16$ matrix (where M is the current number of keypoint tracks).
    - Instead of recording $c_m{}^{i-L_m}$ and $T_{WC}{}^{i-L_m}$, you can alternatively compute and store a 3D *bearing vector* $b_m{}^{i-L_m}$ (express it in the world frame), which will encode directly the direction of the 3D ray corresponding to $c_m{}^{i-L_m}$. In that case, you will also need to store the 3D position of the camera center (expressed in the world frame).

Triangulation

- Use the linear triangulation algorithm developed in exercise 5 to triangulate new landmarks.
- Triangulability check: a simple way to check whether a keypoint track is ready for good triangulation is to check the angle between the bearing vector of the first observation,

and the current bearing vector. If it is above some threshold, triangulation will be likely to yield a good 3D landmark).

- You can be pretty sure that a landmark triangulated behind the camera is incorrect; discard it.

General hints

- In general, proceed step by step and verify your intermediate results visually. Concretely, make sure matching, localization and landmark propagation work properly before triangulating new landmarks.

- We have given pseudo-code indicating what you should do on a keypoint-per-keypoint basis, for clarity. Of course, you should batch these operations for all keypoints. The page Mastering indexing in Matlab will be very handy for this. We strongly recommend to read ALL of this. Note that indexing can be used both on the right and the left hand side of assignments. Also note that you can index recursively: If you have e.g. A = [1 12 14 17], then B(A([2 4])) will access the 12th and 17th elements of B. Note that this might not work as expected when A is a logical index - use the *find* function in that case.