Project Rawseeds

Self-Localization Error (SLE)

recommended performance measure

Note: what follows is based on the concepts defined by the document "General concepts and definitions for BPs", which is part of the information associated to all Benchmark Problem instances. Please refer to that document for clarification.

Introduction

The Self-Localization Error is a recommended measure, i.e., its computation is encouraged but is not necessary for a Benchmark Solution to be considered valid.

SLE is a *usage-based measure* for the evaluation of the capabilities of SLAM (i.e., Self-Localization And Mapping) algorithms. The term "usage-based" means that SLE tries to capture the quality of a SLAM algorithm by estimating its actual capability to generate a map that, *when actually used for real-world applications*, proves to be valid. Usage-based performance measures for algorithms in robotics, such as SLE, are not commonplace, and are not applicable to every domain. However, they can offer a novel way of evaluating algorithms that is both valid and complementary to the traditional approach, i.e., the application of a predefined set of evaluation criteria to the output of an algorithm. Most performance measures (including those defined by Rawseeds, excepting SLE) follow the traditional approach.

The aim of SLE is the evaluation of the overall quality of a SLAM algorithm by actually *using* its output, i.e., the map of an explored environment. Such usage is done under conditions that are as near as possible to a real application scenario. Precisely, a self-localization algorithm is used to localize the robot in the map generated by the SLAM algorithm, while receiving as its input a set of sensor streams recorded by a robot moving in the same environment observed during mapping. To avoid unwanted correlations, the dataset used to perform SLAM and the dataset used to perform self-localization are different.

To sum up, the computation of SLE requires two separate steps:

1. a SLAM algorithm is applied to a dataset, generating a map;
2. a self-localization algorithm is applied to another, different dataset, with the task of localizing the robot in the map produced at point 1.

As previously said, SLE is a performance measure aimed at evaluating SLAM algorithms: the specific self-localization algorithm used for the map-usage phase should be regarded conceptually as of secondary importance, though its choice influences the actual results. For this reason, the proposer of the SLAM algorithm under test (henceforth called **SLAM AUT**) is invited to select a self-localization algorithm that she deems optimally suited to the specific properties of the type of map generated by her SLAM algorithm, in order to best exploit the results of the SLAM AUT.

Preparatory operations

Before proceeding to compute SLE for a SLAM algorithm, it is necessary to select a self-localization algorithm to be used in the second part of the computation. As previously said, the chosen algorithm should be optimally suited to exploiting the kind of representation of the environment produced by the SLAM AUT. In this way, the weight of the latter algorithm in determining the final values of SLE is maximized.

Computation

Each Benchmark Problem instance which recommends computation of SLE for the Benchmark Solutions dedicated to it includes the specification of:

- one dataset to be used to perform SLAM, called ***slamdataset***;
- one or more datasets, called ***localizationdatasets***, to be used to perform self-localization on the map generated by using the *slamdataset*;
- for each of the *localizationdatasets*, a set of one or more ***starting times***, i.e., a set of timestamp values[1].

Now, before giving a formalized description of the process of computing SLE, it is useful to anticipate an overview of such process. First of all, the SLAM algorithm is applied to the *slamdataset*. The self-localization algorithm is then applied repeatedly to each of the *localizationdatasets*, one time for each *starting time*. For each *localizationdataset* and each of the associated *starting times*, the robot is considered as "appearing" in the explored environment at the time instant corresponding to that timestamp, possessing the map of the environment, but no prior sensor data. From the starting timestamp on, the self-localization algorithm is fed with the sensor data from the given localizationdataset (i.e., the algorithms receives the real-world data recorded by a robot moving through the environment of which the algorithm has a map), and its task is that of performing self-localization on the map. As soon as the robot enters an area covered by the ground truth associated to the *localizationdataset*, i.e., as soon as the real position of the robot is known, this position is compared to that generated by the self-localization algorithm. The result of this comparison becomes part of the SLE.

Let us now give a more formalized operative definition of Self-Localization Error. SLE is computed by following these steps:

1. Apply the SLAM AUT to the *slamdataset*, thus generating a map of the environment.

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1 Please remember that each data sample from Rawseeds' data streams is associated to a *timestamp*, i.e., a time data generated by the data-collection robot at the time of recording. The timestamps for all the data streams belonging to the same data-collection session are synchronized.

2. Express the map in the same reference frame used for the *poseGT* ground truth[2].
3. For each *localizationdataset* and each *starting time*, do as follows:
   - feed the localization algorithm with the map and with the sensor data of the *localizationdataset*, starting from the timestamp specified by the *starting time*: the task of the algorithm is to reconstruct the position of the robot in the map (heading is not used to compute SLE);
   - for every timestamp in correspondence of which a sample of the *poseGT* ground truth data is available:
     1. compute the position of the robot (in the ground truth reference frame) with the localization algorithm;
     2. compute the geometric distance D_k (expressed in metres) between the computed position and the position of the robot as specified by the poseGT.
4. Compute the following numerical values:
   - $\bar{D}_k$, mean value of the distances { D_k };
   - σ_{D_k} , standard deviation of the distances { D_k };
   - $a_{D_k, 3\sigma}$ and $b_{D_k, 3\sigma}$, extremes of the 3σ confidence interval of the distances { D_k };
3. SLE = [$\bar{D}_k \quad \sigma_{D_k} \quad a_{D_k, 3\sigma} \quad b_{D_k, 3\sigma}$] ^{T}.

Please note that the computation of SLE requires that the self-localization algorithm is able to provide a position for the robot for *any timestamp when the poseGT is available*. This is not guaranteed to happen, of course. Therefore, for the timestamps when robot localization data are not available, a suitable interpolation algorithm must be used to derive an estimate of the robot's position from available (and/or previously computed) data. The choice of such algorithm is arbitrary, but have to be thoroughly documented (please see section "Additional information to be provided").

It is also useful to note that - after a given *starting time* - there could be more than one poseGT time intervals, possibly not contiguous in time. For the evaluation of SLE, it is required that the pose of the robot is evaluated in all of these time intervals.

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2 The alignment of the reconstructed map to the reference frame used for the poseGT data associated to the explored environment is necessary to allow later comparisons between the reconstructed and actual (i.e., coming from the ground truth) position of the robot. Possible methods to perform such alignment are described by a document specifically dedicated to that issue.

Additional information to be provided

Whenever a Benchmark Solution includes the Self-Localization Error, it is also required to include the following information:

- A full description of the interpolation method used to generate the pose of the robot in the time intervals when poseGT is available but the self-localization algorithm is not able to localize the robot. The term "full description" refers to a description that is sufficiently complete to let any interested (and technically competent) reader replicate the described process.
- For each of the couples {*localizationdataset*, *starting time*} used when computing SLE: a text file including the translational components of the robot poses reconstructed by the self-localization algorithm, evaluated in all time instants t_j when poseGT is available that are subsequent to the *starting time*.
  Each file must have a name which includes both the name of the *localizationdataset* and the timestamp used as *starting time*. Such file must use the same data format adopted for poseGT files, i.e., the so-called *comma-separated values* (csv). The data of each line must be in the form $< timestamp_j, x_j, y_j >$. $timestamp_j$ is the timestamp associated to time instant t_j (as specified by the poseGT).
  Please remember that all poses must be expressed in the PoseGT reference system.