Here are few proposed project ideas. They are roughly in the order of our estimation of their doability. Especially project 2 requires at least some implementation of project 1, so it would be a natural continuement.

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**Project idea 1:**

Visual SLAM combined with deep learning-based place recognition for loop closure detection and comparing its benefits to traditional methods.

**Problem Definition**

Loop closure detection is a very important part of the SLAM problem. Wrong loop closure detection can cause hazardous problems in localization as well as in map building. Also, nowadays traditional methods are not capable always to detect loop closures when for example weather conditions change. For this particular reason, we propose to develop a deep learning-based method for accurate loop closure detection.

**Proposed method to solve the problem**

Two different deep learning methods will be developed to solve the problem defined earlier. First, we propose the method of using CNNs to detect loop closures. Pretrained or hybrid net is used. Obtained features from the net can be used to calculate a similarity score which indicates if obtained two feature vectors are from the same location. Also at least on the first point, for example, PCA might be used to reduce dimensionality since it has shown good results in earlier studies. A good reference to follow will be this (Zhang et al., Loop closure detection for visual SLAM systems using convolutional neural network, https://ieeexplore.ieee.org/document/8082072)

As a second method, we propose to use variational autoencoders since it enables the possibility to train networks in an unsupervised manner. A good reference to follow at first will be for example Geo and Zhang (Unsupervised learning to detect loops using deep neural networks for a visual SLAM system https://www.semanticscholar.org/paper/Unsupervised-learning-to-detect-loops-using-deep-Gao-Zhang/941c8fa86a42806bdb671c33c82d173a4548bc7c#paper-header)

**Expected outcome**

As an expected outcome, our proposed method is able to detect loop closures also in ever-changing conditions.

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**Project idea 2: Better data-association using deep learning (continuement for project 1)**

Front-end of a SLAM system is responsible for associating a measurement to a correct landmark; This is called data-association. Sometimes providing an initial guess for the 3D-location of the landmark can also be taken as part of this task.

**Problem definition**

Failure in data-association is one of the main sources of failures of a SLAM system: 1. erroneous measurement-state matches (false-positives) result in wrong state estimates when fed to the back-end, 2. incorrect rejection of matches (false-negatives) result in poor estimation accuracy.

Short-term data association (matching of visible objects in consecutive frames) is the easier task to tackle and can be done quite reliably with traditional tools (SIFT + RANSAC). Initialization of the landmark location can be done by triangulating the position of the landmark from multiple views.

Long-term data association is more challenging and involves loop-closure detection (Project idea 1) and validation. This validation step requires again matching visible objects, but is harder due to inherently larger difference in the poses of the objects (in addition there can be changes in illumination etc.).

**Proposed methods to solve the problem**

To make the feature matching more robust, we could use features derived by Convolutional Neural Networks (CNNs). On implementation details, we can look at “Image Feature Matching Based on Deep Learning” (Lie et al., 2018). The CNN could be chosen as one of the freely available models achieving high performance on ImageNet dataset (ResNet, Inception, VGG etc.). We could then compare the performance achieved with these features to performance with SIFT-features for example.

**Expected outcome**

If there are objects in the scene that are included in the ImageNet dataset (which spans over 20,000 categories), we expect the extracted features to result in much better feature matching.

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**Project idea 3:** SLAM implementation for time-varying maps to enable long term SLAM.

**Problem Definition**

SLAM methods are usually developed to handle only static maps. However most interesting SLAM problems include time varying world maps since the real world is dynamic. For this particular reason, the goal of this project is to develop SLAM method that is able to handle dynamic environments and enable life-long mapping.

**Proposed methods to solve the problem**

SLAM implementation for time-varying maps requires for example some kind of time varying Pose Graph methods as introduces for example in <https://www.cs.cmu.edu/~kaess/pub/WalcottBryant12iros.pdf>. This reference would be good starting point to understand basics of time varying pose graphs.

Other reference also offer filter based solution where the goal is to map the static part of the scene, after removal of the dynamic objects. Reference for this for example: <https://arxiv.org/pdf/1806.05620.pdf>

**Expected outcome**

As an expected outcome the developed method is able to handle dynamic environments to some extent.

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