Title: Hybridisations based on visual information for the localisation of self-driving cars

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Abstract:

Localisation is a mandatory function of the self-driving car. The car needs to locate itself relatively to its close environment in order to ensure basic driving : staying in the middle of its lane, stopping at the traffic light, overtaking another car, … And it also needs more global localisation in order to choose the right directions and roads to follow to reach the destination wished by the user.

The highest precision needed for the localisation system of an autonomous car is about a dozen of centimetres. This requirement must be fulfilled all the time, in all weather conditions, on all the roads (including urban canyons where GNSS is neither accurate, nor reliable). This level of accuracy is not reachable with state-of-the-art INS-GNSS localisation, and extra information is needed. For anti-collision purposes, autonomous cars will be equipped with several cameras and LIDARs which can bring information on the movement, and hence the localisation of the car.

Safran is developing four different hybridisations based on visual observation for the autonomous car in a cooperative project with Valeo:

- Based directly on extracted characteristic features, as in classic VISUAL SLAM applications
- Based on visual odometry (inferred from extracted characteristics features thanks to a Bundle Adjustment algorithm for example)
- Based on visual beacon recognition
- Based on visual map matching with a local map built from LIDARs and cameras and precise 3D a priori map

These observations can be combined in a unique data fusion algorithm (an Extended Kalman Filter for Safran) but the first two cannot be used at the same time (as they come from the same basic information).

For the hybridisation based on the extracted characteristic features it is needed to add in the state vector a representation of the features. Safran uses classically the inverse-depth parameterisation in order to have an initial error distribution of these components of the state vector as close to a Gaussian distribution as possible. Thus this parameterisation is better suited to an Extended Kalman Filter than the euclidean parameterisation. A maximum number of 15 features are taken into account. It is a good trade-off between the size of the state vector (and the numerical problems associated) and the amount of information needed for the filter to converge fast.

Visual odometry delivers an estimation of the rotation and of the pseudo-translation (the scale factor is unknown) between the first and last images taken into account. The solution chosen by Safran is to add in the state vector the pose of the system at the time when the first image is taken. From a theoretical point of view, this hybridisation is less optimal than the previous one, but easier to implement in a classical localisation filter.

For the autonomous cars, the visual beacons chosen by Safran are Road signs. Safran decides to use extraction and classification algorithms based on neural network. This algorithm is helped by data from a precise map including road signs position and by the localisation estimated by the localisation filter. The directions in which the road sign is seen and the a priori position of this road sign extracted from the map are then transmitted to the localisation filter for the update. Theoretically this hybridisation allows the localisation system to reach a localisation precision as high as the precision of the localisation of the beacons.

It is more and more admitted than autonomous cars will have a precise 3D map embedded. This map can also be used for localisation purpose. Thanks to the numerous perception sensors (LIDARS, cameras, …) integrated on the car, it is possible to build a map of the environment surrounding the car. This “local map” can then be correlated with the a priori map to estimate the pose of the car. This correlation can be used using TriCP algorithm for example. This estimation is then used in the localisation filter. As for the hybridisation based on beacon, the reachable position precision is about the one of the map.

These two last hybridisations do not need to add components to the state vector.

The theoretical models of these four hybridisations based on visual information are presented and the projections of their performance for the self-driving cars localisation are illustrated with simulations results.

As observations based on visual sensors are highly non-linear, inconsistencies can occur when they are processed by an Extended Kalman Filter. It is however possible to add securities in the algorithm in order to avoid this issue. Some of them might be presented in the paper and the presentation.