Real-time Visual Self-localisation in Dynamic Environments

A case study on the Off-road Platform RAVON

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Abstract In this paper a real-time approach for visual self-localisation of mobile platforms in dynamic environments is presented. Vision-based approaches for improving motion estimation recently have gained a lot of attention. Yet methods banking on vision only suffer from wrong tracking of features between frames as the optical flow resulting from the robot motion cannot be distinguished from the one resulting from robot independent motion in the camera images. In the scope of this work a method for robust visual self-localisation in dynamic environments on the basis of feature prediction using wheel odometry was developed.

1 Introduction

One of the key problems in mobile robotics is the localisation of a vehicle in unknown terrain. In recent years visual methods for pose estimation have become more and more interesting as they are now computationally feasible and do not suffer from the same sources of error as traditional approaches do. In fusion with other systems the robot pose estimation should become more stable in particular on the local level.

Figure 1. RAVON, the Robust Autonomous Vehicle for Off-road Navigation.

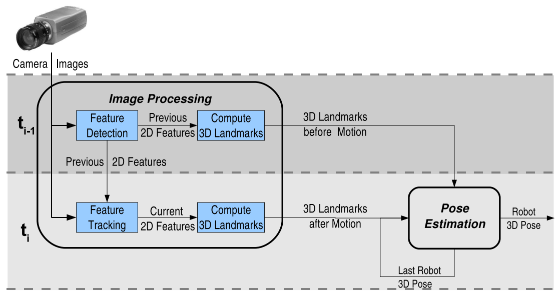

Figure 2. Overview of Visual Odometry.

On the mobile off-road platform RAVON[1] – which is developed by the RRLab[2] at the University of Kaiserslautern – wheel odometry, a custom-built inertial measurement unit with integrated digital compass and a GPS receiver have been deployed so far. Now this suite of sensor systems shall be complemented with stereo ego motion in order to improve the local stability of the yielded pose information. Besides better results of the fused position information this extension opens the possibility to build up an absolute local obstacle map from stereo vision information in order to cover the blind angles of the camera system. In principle most visual odometry approaches follows the pattern outlined in Figure 2. The camera system captures a frame and a set of features that are suitable for tracking are selected in this image. After some time, another frame is taken. The features that have been detected in the previous frame are now tracked into the current frame. The vectors between these points contain the information about the change in orientation and translation of the robot between the two subsequent frames. The last step is an ego-motion estimation on the basis of the vectors to receive the robot pose according to a given starting point.

2 State of the Art

The idea of visual odometry was first developed by L. Matthies [Matthies 89]. This approach was refined and deployed on several mars robots [Cheng 05] and other researchers implemented different flavours of the original concept. The differences mostly lie in the camera system – monocular [Cambpell 05], omni-directional [Corke 04] or stereo [Matthies 89] – used. The two first mentioned camera configurations are not an option in off-road terrain as a flat ground plane needs to be assumed in order to compute 3D coordinates from the image points. Therefore a stereo-ego-motion approach was chosen for implementation in this work.

In common outdoor scenarios a lot of dynamics come into play as people, other vehicles or tree branches and high grass affected by the wind cause vehicle motion independent movement in the camera images (See Figure 5 in Section 4).

[1] RAVON → Robust Autonomous Vehicle for Off-road Navigation [Schäfer 06]
[2] RRLab → Robotics Research Lab (`http://rrlab.informatik.uni-kl.de`)

Current implementations banking on visual data only (p.ex. [Sünderhauf 06]) suffer from the inability to decide what optical flow is caused by the robot motion and what is introduced by the disturbers mentioned above. In some realisations the vehicle velocity is taken into account in order to prevent pose drift when standing still [Nistér], yet most publications do not cover the problem of dynamic sceneries at all. In [Helmick 04] the research group around L. Matthies introduces the idea of using the wheel odometry to filter wrong optical flow. The system in question was to be deployed on martian rovers and optimised for operation in stop-and-go mode. Furthermore the aspect of dynamic environments was not addressed as the worlds out in space appear to consist of rocks and deserts.

3 Visual Self-localisation in Dynamic Environments

Having introduced the concept of visual odometry in general and the problems which arise when dynamics come into play this section shall outline the approach implemented in the context of this work. The idea of incorporating wheel odometry into a filtering step for pose estimation was picked up and integrated into a real-time visual odometry system. The focus in this context was the development of a visual self-localisation system which would be robust against dynamic disturbers in order to obtain locally stable pose information. On this basis an absolute local map shall be built of obstacle detection output computed from the very same images as used for pose estimation.

The implemented system can be grouped into three modules (See Figure 3). Module *Image Processing* encapsulates feature detection and tracking as well as the 3D reconstruction of the landmarks. For `Feature Detection` the OpenCV[3] implementations of the Harris corner detector [Derpanis 04] is used. `Feature Tracking` and `Stereo Matching` steps are carried out with the Lucas-Kanade-tracker [Lucas 81] also available in OpenCV. Given the 3D landmarks of two subsequent time steps (t_{i-1} and t_i in Figure 3) a *Feature Filtering* step is inserted using the `Pose Delta` computed from the correlated 2D poses of the robot

[3] OpenCV → Open Computer Vision Library `http://opencv.sourceforge.net`

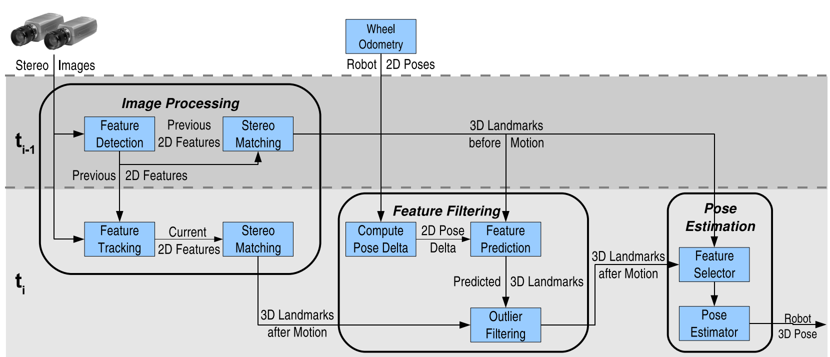

Figure 3. Concept of the implemented Visual Self-localisation Facility.

from the wheel odometry. For *Pose Estimation* a suitable subset of the filtered 3D landmarks is computed using a preemptive RANSAC-based algorithm in combination with Singular Value Decomposition for computing the robot pose delta. The preemptive error function for RANSAC termination is computed from the reprojection of the transformed previous 3D landmarks into the image plane. Due to space limitations in this paper the reader shall be referred to [Hahnfeld 07] for the mathematical details. The attempt to fuse wheel odometry with visual odometry implies that both sources of information need to be synchronised. On the test platform RAVON stereo image processing runs on a dedicated computer system as it is computationally quite expensive. In order to correlate sensor data from different sources all computers are synchronised via the network time protocol which assures an accuracy of about 2-10 ms in a controlled network. This is given as RAVON features a switched network with only four computers connected. Furthermore traffic is limited by trying to compute as much as possible on the particular nodes owning the data source and only transmit filtered abstract representations over the network rather than raw sensor data [Schäfer 05]. The wheel odometry poses are computed from encoder data coming from a DSP attached with a time stamp. This time stamp is adapted to the system time and attached to the odometry pose. The same is done for the image data which come with internal time stamps from the cameras. That way both data sources are brought to the same time basis very early in the procedure. The odometry poses with the attached poses are placed into a ring buffer located in a shared memory. Every time new camera images are available the ring buffer is searched for the best timed odometry pose. In order to give the odometry pose collector facility enough time to place the current pose into the ring buffer and to transfer the data over the network the poses are fused with the images after an undistortion step which is necessary for precise stereo imagery.

4 Experimental Results

In this section some experiments carried out on the RAVON and in the simulation environment [Braun 07] developed at the RRLab shall be presented. First of all the parameters for optical flow computation were tuned in the simulation environment where no mechanical or optical inaccuracies are present (imprecise mounting of the cameras on the robot, defective position of the CCD's in the cameras, lens distortion, etc.). Furthermore no disturbers falsify the input images and therefore perfect conditions for optimising the optical flow component. As a benchmark for this procedure the track depicted in Figure 4 (a) of about 20 m was defined. Step by step the parameters were adjusted according to the best performance in comparison to ground truth which is naturally available in simulation. With the optimised system the endpoint deviation was about 1.75 % which corresponds to a distance of 0.38 m. In average the deviation of the estimated points compared to ground truth was about 0.15 m.

The parameters for optical flow computation set real experiments were carried out to test the influence of disturbers. Figure 5 shows the same images as

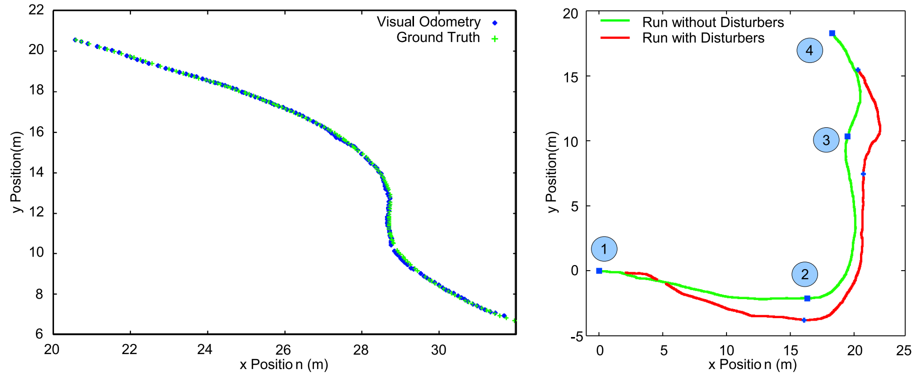

Figure 4. Visual odometry compared to ground truth in simulation (left) and Visual odometry test runs on RAVON with and without disturbers (right).

introduced in Section 2 as examples for robot motion independent movements in the camera images. In these illustrations the reader can see that the optical flow introduced by the disturbers was classified as wrong optical flow which will not be taken into account. For clarity reasons the frames have been chosen such that the disturbing regions are not very large. In several test runs it was shown that external influences may occupy large regions without affecting the accuracy of the visual self-localisation.

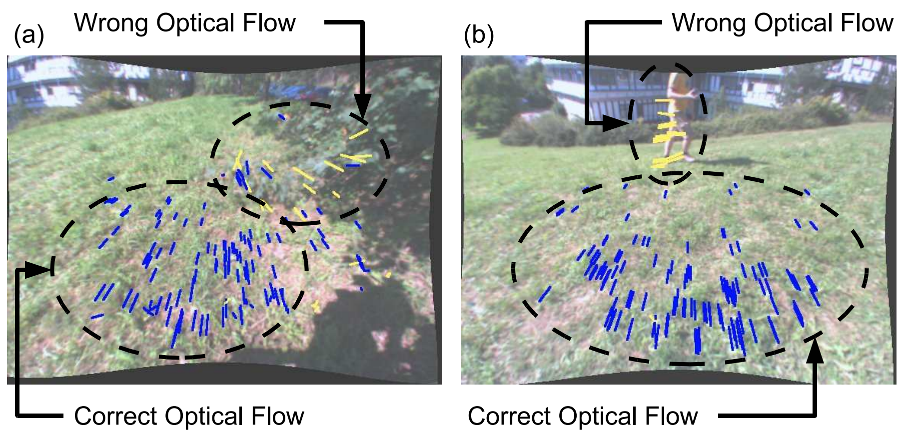

Figure 5. Wrong optical flow correctly classified by the implemented system (yellow/light grey lines). Only the correct optical flow (blue/dark grey lines) is used.

In a first set of tests a course was marked on the test grounds of the RRLab. This course was covered twice, once without and once with disturbers. At the predefined check points the position computed by the visual odometry was tagged in order to compare these spots later. Note that a quantitative conclusion on this type of test is difficult as repeatability of the very same run cannot be achieved. Nonetheless the plot in Figure 4 (b) shows that the computed poses with disturbers stay locally stable and the deviation of both runs is in a promising range. Over the whole run the deviation is about 10 % of the distance covered (15 m (checkpoint 2): 1.75 m, 30 m (checkpoint 3): 3,22, 40 m (checkpoint 3): 3.51 m) but this basically results from one minor orientation error in the very beginning which accumulated over time.

In order to get quantitative results ground truth comparisons using a powerful DGPS receiver as a reference would be necessary. As such a system was not available on RAVON until now these experiments are still pending. In the near future a StarFire2 GPS receiver which reaches a positioning accuracy of about 10 cm using the commercial satellite correction network Green Star will allow to carry out that kind of test. GPS receiver and Green Star license will kindly be provided by John Deere.

5 Conclusion and Future Work

In this paper a real-time stereo-ego-motion system for application in dynamic environments was presented. The idea of incorporating wheel odometry information to filter wrong optical flow was picked up from approaches approved in stop-and-go mode without dynamic sceneries in space robotics. In that context a method for careful correlation of stereo images and wheel odometry was introduced which results in a robust real-time stereo-ego-motion system. In particular the ability to distinguish ego-motion-born optical flow from the one introduced by disturbers makes the system suitable for dynamic environments. Experiments on the off-road platform RAVON showed that locally stable pose information can be achieved in dynamic environments.

In the future ground truth comparisons shall be carried out using a new high precision DGPS receiver. In that context the impact of further cascaded filtering mechanisms of the optical flow shall be evaluated. RAVON features an obstacle detection facility which uses the same stereo images as the pose estimation. In the future both systems shall be brought together in order to build an absolute local map to cover the blind angles of the camera system for obstacle avoidance. To assure optimal adjustment of the stereo camera head for obstacle detection an off-road-adapted pan/tilt unit was developed in recent months. Now that the mechanics are ready this active vision unit will be integrated into the existing framework. The camera head movement needs to be taken into account in pose estimation. Here again precise correlation is necessary to yield satisfactory results. The authors assume that the presented correlation approach already covers the problems that could arise with the new degree of freedom.

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