Power-aware Fusion of Visual and Wheel Odometry for Mobile Platforms

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***Abstract*—A new approach is presented to estimate the motion of a mobile platform using a fusion of visual odometry (VO) and wheel odometry (WO). An Extended Kalman Filter is used with an augmented state vector including the wheel slip. The new approach allows for flexible use of VO, which is central to slip estimation but consumes significant electrical power. The approach can be used in the future to adaptively optimise the number of VO measurements.**

Keywords—mobile platform, Visual Odometry, wheel slip, Extended Kalman Filter

I. Introduction

Autonomous navigation on other solar system bodies, like Mars, face many interesting challenges. One of the critical problems is precise localisation. Without easy access to on-demand global position measurements, relative localisation techniques, such as Visual Odometry (VO), are of the essence. Furthermore, VO has the additional benefit of allowing to measure wheels slip which in case of Mars can contribute to over 10% of error in the position estimate [1]. Precise and beneficial as it may be, VO requires considerable computation effort and relies on good illumination, resulting in significant electrical power demand. For a Mars rover, just like for any spacecraft, the power budget is carefully balanced, and it cannot spend any more energy than estimated. For future Mars missions, such as European's Sample Fetch Rover, the rover is expected to drive for much longer distances than any other remote missions to date [2]. This objective poses another technical challenge of how to minimise energy usage while maintaining accurate localisation and maximising distance travelled. In this paper, we use a novel Extended Kalman Filter formulation to explore the trade between VO use and navigation accuracy.

II. Related Work

Many different algorithms and strategies may be employed to optimise energy usage and increase localisation accuracy. In their work, NASA presents how VO measurements taken by Mars Exploration Rover (MER) and Mars Science Laboratory (MSL) rover are used to estimate slip and support trajectory control [3], [4]. Different power optimisation strategy was presented in [5] where the optimisation was achieved by introducing an intelligent controller to command wheels based on the soil type. This approach requires parameters tuning but may lead to a more efficient drive. Another solution is to recognise terrain in front of the rover to adapt to the scenery. So far this has been presented as either prediction of slip for better trajectory planning, where rover can avoid high-slip areas to preserve energy, [6] or the overall scenery classification to switch between different sensors which may either optimise energy usage or increase localisation precision [7].

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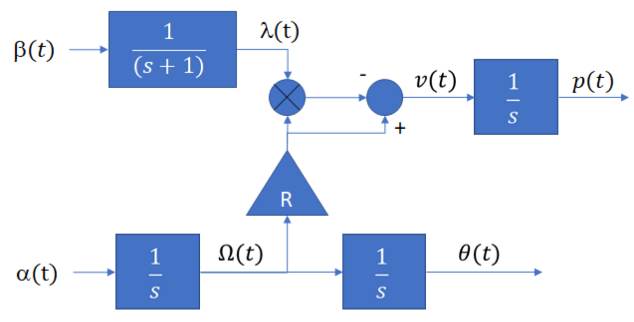

Fig. 1 Block diagram of the proposed model

Often VO is used to estimate wheels slip. In [8] authors present how slip can be estimated using Inertial Measurement Unit (IMU); however, in their approach, calibrated wheels angular velocity is still fused with VO.

III. Approach

The proposed model represents only 1D motion and is presented on Fig. 1 with p being the position, v – velocity, θ - wheels accumulated angle, Ω - wheels angular velocity, λ - slip, and R – wheels' radius. Both α and β are treated as process noises that drive the model, where α is interpreted as wheels angular acceleration and β describes the terrain. The system has been discretised with a step size of 0.1 s with state vector defined in (1).

$$x(t) = [p(t)\ \theta(t)\ \Omega\ (t)\ \lambda(t)\ m(t)]^T \tag{1}$$

To model VO, the state vector is augmented with m, defined as the position at which the last VO image was recorded:

$$m(t^+) = \begin{cases} p(t) & \text{if VO measurement at time t} \\ m(t) & \text{otherwise} \end{cases} \tag{2}$$

Then the two odometry measurements (wheel odometry (WO) which measures wheels accumulated angle and VO which measured delta position) are expressed as:

$$y_{WO}(t) = \theta(t) + \varepsilon_{WO}(t) \tag{3}$$
$$y_{VO}(t) = p(t) - m(t) + \varepsilon_{VO}(t) \tag{4}$$

where ε denotes the respective measurement noise and noting that the VO measurement is not taken at every update.

Wheel slip is modelled using a first-order filter driven by an unknown process noise. This approach means the slip uncertainty grows with time, but not unboundedly as a random walk, and has a tuneable 'forgetting' factor to capture the variability of terrain. The gain parameter of the filter was set to one as it is a scaling factor for the β noise, which models all-terrain properties related to the slip. To simplify this evaluation, we assumed no skidding or breaking; therefore, the slip is defined as presented in (5).

$$\lambda(t) = 1 - v(t)/\ [R^*\Omega\ (t)] \tag{5}$$

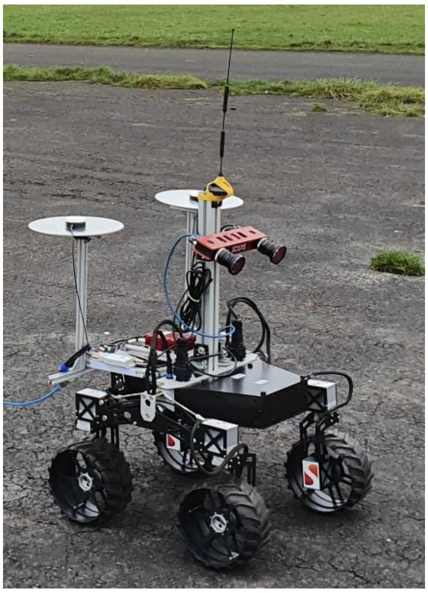

Fig. 2 Mobile platform used for experiments.

IV. Results and Discussion

The model has been validated using data from real-world experiments where Mars-like rover with Real-Time Kinematic (RTK) GNSS for ground truth (as presented on Fig. 2) was driving on two different types of terrain: tarmac and grass. All graphs from Fig. 3 present sets of trajectories that lasted for 500 s. The rover speed was 0.2 m/s, and WO measurements were done at approximately 10 Hz frequency. Graphs on the left-hand side present how changing VO update rate impacts estimated position errors and their three standard deviation (3σ) boundaries. All trajectories, except for one which happened on a hilly grass terrain, are always within estimated precision. Performing VO measurements more often (e.g. Fig. 3 VO @ 0.2 s) leads to narrower three standard deviation boundaries due to high frequency of precise position measurements. With decreased VO update rate (e.g. Fig. 3 VO @ 3 s), the model maintains its accuracy for most of the trajectories; however, errors tend to be greater since the filter leans more towards WO estimates. Graphs on the right-hand side present how changing σ_β affects position estimation. Low values (e.g. Fig. 3 σ_β=0.01) indicate relatively constant slip, and therefore the filter prefers to trust WO measurements more. In this case, VO is mainly used to measure the slip value indirectly. On the other hand, high σ_β value indicates terrain where slip may change dynamically, therefore the VO measurements are preferred (e.g. Fig. 3 σ_β=2). Also, because of more dynamic changes, more noise into position measurements is introduced, which is visible as saw-tooth on three standard deviation boundaries.

V. Conclusions

This paper presents a new model for fusing wheel and visual odometry on a mobile robot. We successfully validated the proposed model against the real-world data captured using representative Mars-like rover. The results suggest that the model correctly predicts navigation uncertainty levels as the frequency of VO measurements change. Further research will use this model to pursue an adaptive controller capable of optimising the number of VO measurements to trade accuracy against electrical power usage.

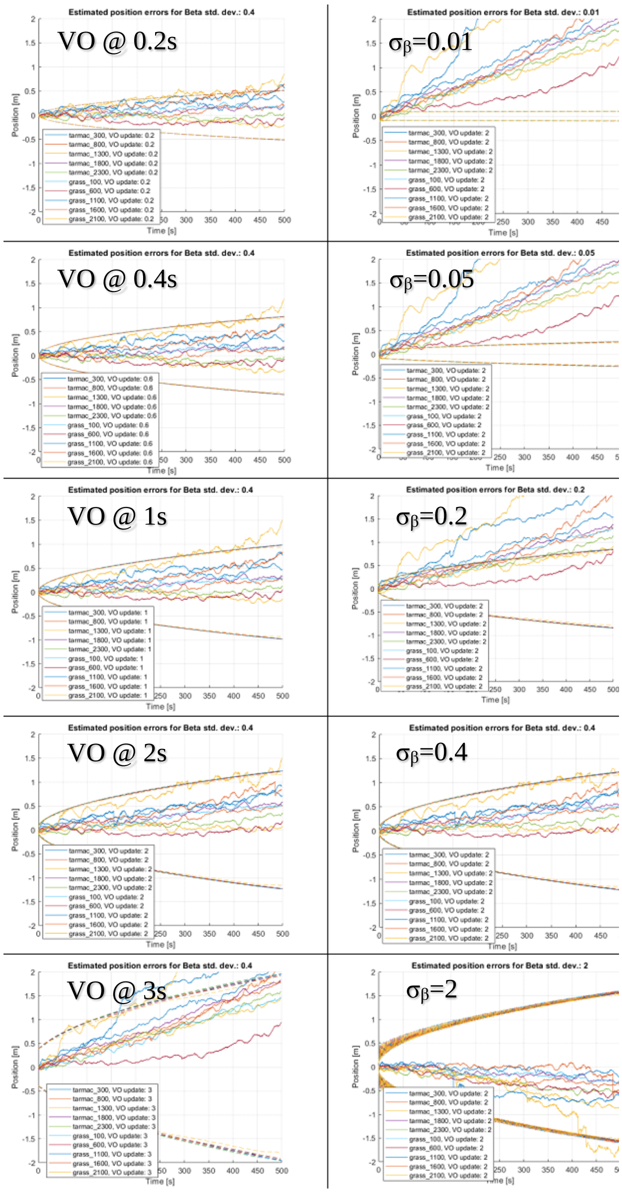

Fig. 3 Position estimation errors for varying VO update time (left-hand side) and β standard deviation (right-hand side).

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