Multibody-based state observer for navigation applications

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More than 1.2 million people die every year due to road traffic injuries, being also the main cause of mortality among people aged 15-29 years [1]. A great research effort was motivated for this reason over the last years, resulting in several aids that make automobiles safer as they can assist the driver under some emergency situations. Autonomous vehicles go one step farther: they do not help the drivers, but replace them.

Driving aids rely on information about the vehicle. When possible, this information is gathered by sensors, but it is not always possible due to technical or economical reasons. State observers overcome this problem by combining data from sensor with predictions produced by a model. A detailed model (e.g. a multibody model) can provide more information about the state of the whole vehicle. The absolute positioning of the vehicle is still a problem to be solved. As a first implementation of multibody-based state observers, this work is focused on the navigation issue.

Usually, a GPS is employed as the absolute positioning sensor, and it is aided by inertial, odometric, and optic sensors. Several algorithms can be used to combine the information coming from the sensors, although different variants of the Kalman filter are usually implemented as state observers for navigation purposes [2]. However, none of these techniques can provide accurate estimations of the absolute position of the vehicle when the GPS is not available for some time, for example due to trees, buildings, or tunnels.

In this research, inertial and odometric sensors are combined with a GPS to correct the state of the multibody model of a vehicle. This way, the predictions from the multibody model can be used as virtual sensors. The multibody model can extend the accuracy of the navigation solution for longer times when the GPS is not available, since the multibody model provides good results, even before the corrections from odometric and inertial sensors are applied. When the GPS is available, it is also used to correct the state of the model. In order to check the algorithm behavior, some maneuvers were performed with a prototype (see Fig. 1), and experimental data was gathered. The sensors installed in the prototype are listed in Tab. 1.

Fig. 1: Prototype vehicle

The algorithm used for the integration of the different sensors is an error state formulation of the Kalman filter (see e.g. [3]). This method was first proposed for multibody models in [4], and it has demonstrated that it can provide better estimations than other conventional Kalman filters, with a lower computational burden.

An additional advantage of the method is that it is easier to implement over already existent multibody models, since the dynamical model is outside the filter, as shown in Fig. 2, thus allowing us to use a newer version of the

Measured magnitudes	Sensor
Vehicle accelerations (X,Y,Z)	Accelerometers
Vehicle angular rates (X,Y,Z)	Gyroscopes
Vehicle tilt angles (X,Y)	Inclinometers
Wheel rotation angles	Hall-effect sensors
Brake line pressure	Pressure sensor
Steering wheel and steer angles	Encoders
Engine speed	Hall-effect sensor
Steering torque	Inline torque sensor
Throttle pedal angle	Encoder
Rear wheel torque	Wheel torque sensor
Position, speed and course	GPS receiver

Tab. 1: List of installed sensors.

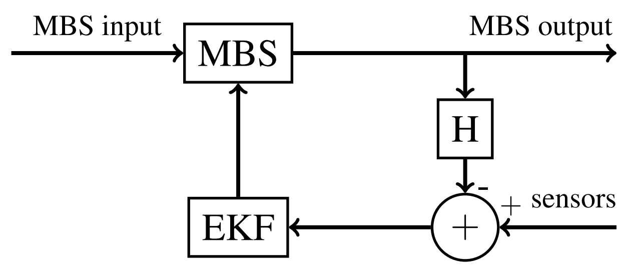

Fig. 2: Simplified flow diagram of the error state Kalman filter applied to multibody simulations

model validated in [5]. The multibody model is run without changes, while the filter estimates the errors in the multibody states. Then, the states of the multibody model are corrected with the estimations provided by the filter. Although the multibody model was modelled using natural coordinates, the Kalman filter estimates the errors of the degrees of freedom of the mechanism. Therefore, the corrections are projected over the constraints manifold in order to fulfil the constraints of the multibody system.

The algorithm employed in this work was used here only as a navigation tool. However, all the states of the multibody model are available, so they could be employed for any other purpose, such as advanced stability controllers, or active roll control systems.

References

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