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Innovative Management of Wheel-Rail Adhesion Conditions in Localization Algorithms for the Automatic Train Protection

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In the modern railway network, Automatic Train Protection and Control (ATP-ATC) systems are fundamental to increase the infrastructure capacity, maintaining a proper level of operation safety. Odometry is a relevant on-board module, since it estimates the speed and the travelled distance of a railway vehicle along the track. Its reliability affects the definition of allowed speed profiles, in order to prevent collisions from a driver's failure to observe a signal. Typically the dead reckoning relies on encoders providing an accurate estimation of the train speed only when good adhesion conditions between wheel and rail occur. In presence of wheel sliding the estimation error may become very high.
In this paper the management of adhesion conditions is enhanced using an Inertial Measurement Unit (IMU) which improves the adhesion condition detection and the speed and travelled distance estimation.
The testing of the proposed algorithm is performed through a testing simulator, set up by the MDM Lab and used to speed up the algorithm tuning, capable of replicating in a realistic way the motion dynamic effects of a railway vehicle on inertial sensors. The Hardware-In-The-Loop test rig is composed of a Matlab-Simulink™ three-dimensional multibody model of a railway vehicle, a commercial anthropomorphic manipulator with spherical wrist and an IMU designed by ECM Spa (Pistoia, Italy). The experimental results are compared to the performance requirements fixed by the European Rail Traffic Management System (ERTMS).

1. Adhesion detection in classical localization algorithms

The Dept. of Industrial Engineering of the University of Florence, since many years, worked in collaboration with the Italian Railway Companies (Trenitalia) in the design of the odometry algorithm for the Italian ATP system, named SCMT (Italian acronym for "Sistema Controllo Marcia Treno"), exploiting only data coming from two encoders that measure the axle angular speeds (Allotta et al., 2002).

1.1 SCMT algorithm

Encoders are widely diffused in railway applications due to their robustness and reliability (e.g., they are exploited by the Wheel Slide Protection and anti-skid systems). The wheel peripheral speed can be calculated multiplying the wheel angular speed sensor measure by the wheel radius.

$$v_i = R_i \omega_i \tag{1}$$

The weak point of this approach is the low reliability under degraded adhesion conditions: when the wheel-rail adhesion conditions are degraded and the train is accelerating or braking, pure rolling conditions between the wheel and the rail do not hold any more and macroscopic slidings arise.

$$v_i - R_i \omega_i = \delta_i \tag{2}$$

If the train is accelerating the wheel peripheral speed tends to overcome the train speed ($\delta_i < 0$), conversely ($\delta_i > 0$) during the braking phase.

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For the purposes of the calculation, the wheel-rail adhesion condition management is very relevant: in fact, if it is judged as “good”, the train speed can be evaluated directly from the peripheral speeds of the wheels, otherwise a speed estimate can be obtained by integrating a constant acceleration value, previously established, according to the dynamical performances of the train.
Two criteria are defined to detect the wheel-rail adhesion condition:

- the *tachometric criterion* states that two wheels are sliding if the absolute value of the difference between their wheel peripheral speeds (v_1, v_2) overcomes a fixed threshold (Δ_v):

$$|v_1 - v_2| > \Delta_v \tag{3}$$

- the *accelerometric criterion* compares the wheel peripheral accelerations. A wheel is sliding if the absolute value of its acceleration (a_1, a_2) overcomes a fixed threshold (Δ_a):

$$|a_1| > \Delta_a \qquad |a_2| > \Delta_a \tag{4}$$

The detection of the adhesion conditions shows some weak points: in fact, if both the wheels slide, the possibility that the *tachometric criterion* fails is high. In this case the *accelerometric criterion* should be able to recognize the sliding phase. In the worst-case of sliding of all the wheels with low acceleration, both the criteria may fail. The fake detection of the adhesion condition happens frequently on the railway network, so SCMT algorithm is often affected by non-negligible errors.

1.2 ERTMS solution

Since the operative conditions may vary during train operations, the ability of one isolated sensor to provide accurate reliable data is limited. Sensor fusion techniques allow to reduce the drawbacks of single sensors, combining information coming from independent sources.
The ERTMS system provides for the use of a set of sensors including the same two encoders, a radar sensor and a longitudinal accelerometer. A reliable measure of train acceleration could be very useful to recognize adhesion losses and, in sliding conditions, to estimate the speed by numerical integration, too.
So as provided by the University of Florence (Malvezzi et al., 2010) the adhesion detection is yet based on tachometric and accelerometric criteria. The difference with the SCMT algorithm stands on the second criterion: a wheel is sliding if the absolute value of the difference between the wheel peripheral acceleration (a_i) and the longitudinal accelerometer measure (a_m) overcomes a fixed threshold (Δ_a). So for each axis (i=1, 2) the degraded adhesion condition is detected when:

$$|v_1 - v_2| > \Delta_v \text{ or } |a_i - a_m| > \Delta_a \tag{5}$$

The lack of this solution is related to the not perfect assembly of the sensor and to the presence of vertical or lateral acceleration components due to the line gradient: if the sensor sensitive axis is not perfectly perpendicular to the gravity vector, the output signal is not null, even if the accelerometer is perfectly still.
The effect of the line gradient can be compensated if the information about the gradient were communicated to the onboard subsystem by the balises of the ground signalling subsystem. Unfortunately they provide the track gradient information as mean or minimum value. So the errors due to misalignments or to the track-gradient unreliable estimate cannot be compensated without adding other sensors.

2. Innovative wheel-rail adhesion condition management

The complex localization algorithms for railway vehicles, developed during the last few years, are able to reach an acceptable accuracy on the position and speed estimation, even though they show problems related to the lack on the sliding detection, because of the aforementioned errors.
In order to overcome the drawbacks of each type of sensor and thus improve the quality of the estimate, the use of sensor fusion techniques has been evaluated suitable. Moreover, the development of the Micro Electro-Mechanical Systems (MEMS) technology, in terms of continuous decrease of the price and dimension of the sensors, makes interesting approaching the problem of the train localization with original solutions in the field of Inertial Navigation Systems (INS).
A platform called Inertial Measurement Unit (IMU), composed of a triaxial accelerometer and a triaxial gyroscope, can provide considerable improvements to the localization performance, since it provides the calculation of the attitude of the train. INS algorithms allow estimating the current position of a vehicle by means of the measure of its translational and rotational motion with respect to an inertial reference system.
In classical approaches (Titterton and Weston, 2004), four reference frames are defined: Inertial frame (i-frame), Earth frame (e-frame), Navigation frame (n-frame), Body frame (b-frame).
As in Figure 1, the strapdown INS algorithm (Titterton and Weston, 2004) is composed of an Attitude computation and a Navigation one, where the estimated speed and position of the vehicle are obtained as successive time integrations of the acceleration measurements provided by the accelerometers.

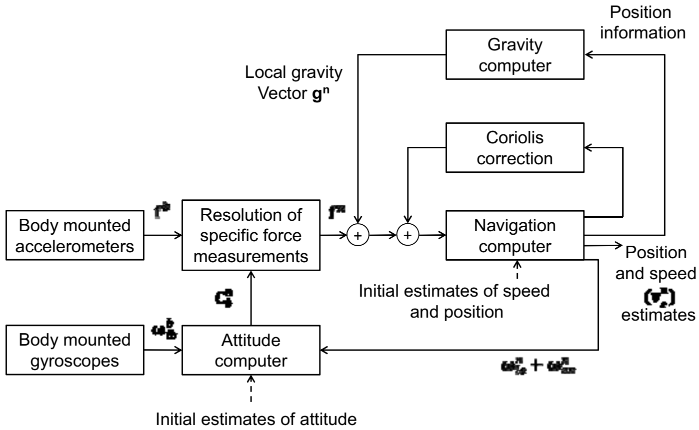

Figure 1: strapdown INS algorithm

2.1 Attitude computation in strapdown INS algorithms

The attitude of the body is required to resolve the specific force measurements into the reference frame, by computing an estimate for the rotation matrix C_b^n:

$$a^n = C_b^n f^b - \left(2\omega_{ie}^n + \omega_{en}^n\right) \wedge v^n + g^n \tag{6}$$

where f^b is the body acceleration as measured by the accelerometer, g^n is the gravity vector equal to [0 0 −9.81]^T and the term between brackets is the sum of Coriolis and centripetal acceleration.

The vector ω_{ib}^b is the turn rate of the body with respect to the i-frame as measured by the gyroscopes. To retrieve the body rate with respect to the n-frame, ω_{nb}^b, the following operation is performed:

$$\omega_{nb}^b = \omega_{ib}^b - C_b^n\left(\omega_{ie} + \omega_{en}\right) \tag{7}$$

where ω_{ie} is the Earth's rate with respect to the i-frame and ω_{en} the turn rate of the n-frame with respect to the Earth. The computation may be based on the Euler angles; refer to (Siciliano et al., 2011) for the nonlinear relationship between the derivatives of the Euler angles and the body angular rates and the C_b^n calculation, based on the Euler angles computed by time integration. The lack of the strapdown INS algorithm is that it blindly processes the raw inertial data affected by errors and, due to time integration performed, introduces errors in attitude $\delta\Phi$, velocity δv and position δp. The orientation error, coming from the integration of the angular rates, causes a wrong projection of the acceleration onto the global axes.

2.2 Attitude computation in the innovative localization algorithm for railway applications

Some preliminary numerical experiments have proved that INS itself, as already anticipated, cannot provide the high accuracy required for velocity and position estimates. So, according to the directives of the sensor fusion techniques, INS is *fused* with the encoder measure. The theory of Kalman Filter (KF), as in (Durrant-Whyte and Barshan, 1995), is suitable to implement the sensor fusion strategy and, as a stochastic filter, can improve the estimation from noisy inputs. As shown in Figure 2, the innovative localization algorithm provides:

- *Orientation Kalman Filter* (OKF) estimates the orientation of the train from b-frame to n-frame in terms of Euler angles, fusing the information of the angular rate coming from the gyroscope with the wheel peripheral acceleration, derived from the tachometer;
- *INS-ODO Kalman Filter* (INS-ODO KF) estimates speed and travelled distance, fusing the gravity compensated body longitudinal acceleration with the wheel peripheral speed.
- *four diamond boxes* detect relevant working conditions (Coasting, Straight, Adhesion, Balise).

It is worth to note that:

- the n-frame is defined as the initial body frame of the train and, for the purposes of the work, the Earth's rate is considered negligible, so $\omega_{nb}^b = \omega_{ib}^b$ and $a^n = C_b^n f^b + g^n$;
- the OKF implements a 3D filter, the INS-ODO KF, instead a 1D one, since the ERTMS requirements (EEIG 059, 2000) are based on the longitudinal speed and the travelled distance;
- the pitch, linked to the track gradient, is estimated in real-time with high reliability, by the OKF.

For a detailed explanation of the whole algorithm refer to (Malvezzi et al., 2013), in this paper the authors prefer focusing on the implemented innovative wheel-rail adhesion management.

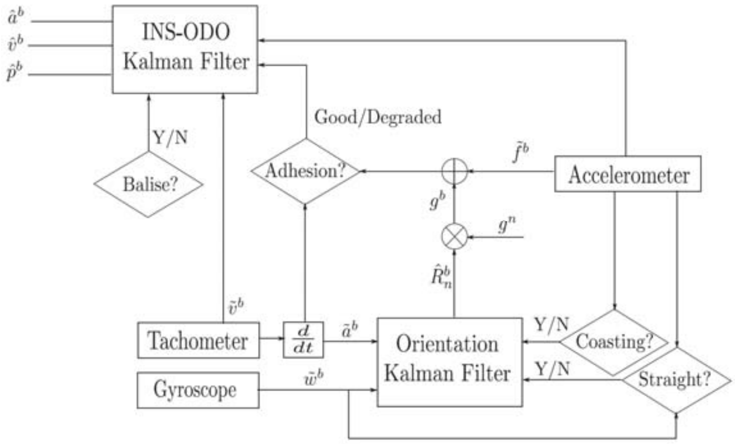

Figure 2: block diagram of the innovative localization algorithm

The "accelerometric criterion" becomes the master one: if the difference between the wheel peripheral acceleration $\left(a_x^b\right)$ and the gravity compensated body longitudinal acceleration $\left(f_x^b - \hat{R}_n^b g\right)$ is less than a threshold (η_{ad}), the adhesion is considered good. In order to avoid that "fake" good adhesion conditions are considered, a slave "tachometric criterion" has been implemented: it allows the speed reset only if the difference between the actual estimated speed $\left(\hat{v}_x^b\right)$ and the wheel peripheral one $\left(v_x^b\right)$ is lower than a threshold (η_v). It is worth pointing out that, compared to the classical SCMT solutions, only one tachometer is sufficient for the detection of the wheel-rail adhesion condition. The equation:

$$\begin{cases} \sigma_{a_x}^2 \quad >> \quad \sigma_{v_x}^2 , \quad if\left(\left|f_x^b - \hat{R}_n^b g - a_x^b\right| < \eta_{ad} \ and \left(\left|\hat{v}_x^b - v_x^b\right| < \eta_v\right)\right) \\ \qquad \qquad \sigma_{a_x}^2 \quad >> \quad \sigma_{v_x}^2 \ otherwise \end{cases} \tag{8}$$

states that, when good adhesion between the wheel and the rail occurs, the measurement update of the KF can rely on the contribution of the speed measures provided by the tachometer (σ_{ax} and σ_{vx} are the standard deviation values of, respectively, the accelerometer and the encoder). The thresholds η_{ad}, η_v have been experimentally tuned in the testing phase.

3. Dynamic simulator for the testing of the innovative localization algorithm

Since the tuning of the innovative localization algorithm involves the simulation of a wide range of working conditions, the testing by means of experimental test runs is difficult and expensive. In order to overcome this problem, a testing simulator, able to replicate in a realistic way the motion dynamic effects of a railway vehicle on inertial sensors, has been implemented.

The dynamic simulator is composed of a mathematical Dynamic Model (DM) which implements a 3D multibody model of a railway vehicle, developed using Matlab-Simulink™, able to reproduce different working conditions and arbitrary tracks (Meli et al., 2008).

Washout Filters (WF) are software components, with the aim, not of reproducing the movements of the vehicle but of inducing the same dynamic effects the pilot would experience in the real scenario. The classical WF strategy splits the reproduction of high and low frequency acceleration (angular rates) components, through high pass and low pass filters:

- High frequency accelerations need a limited space so the simulator reproduces directly the same movement of the vehicle (Direct Linear Motion Strategy);
- Low frequency accelerations, which should need large movements, can be reproduced tilting the simulator, exploiting gravity (Tilting Strategy).

Classical Washout Algorithm (CWA) (Grant and Reid, 1997) is the algorithm used to implement WF. The problem of the adaptation of WFs for the testing of inertial sensors is linked to their higher sensitivity compared to the human vestibular apparatus. To ensure that angular variations, fixed by the Tilting Strategy, do not affect the perception of angular rates, accelerometers and gyroscopes are tested separately.

The control algorithm for the robot is based on a Closed Loop Iterative Kinematic (CLIK) strategy based on the optimization of the manipulability index (Siciliano et al., 2011).

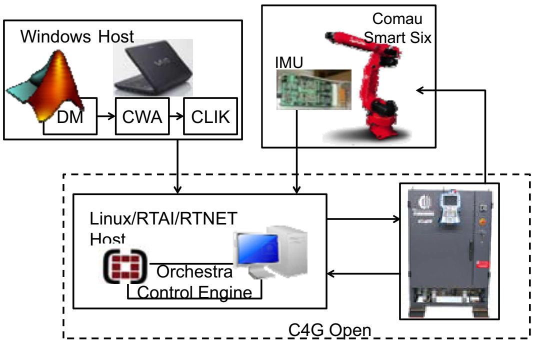

Figure 3: architecture of the HIL test rig

Figure 4: HIL test rig @ MDM Lab, Pistoia

The authors have set-up and tested (Allotta et al., 2012) a Hardware-In-The-Loop (HIL) test rig inside the MDM Lab (Pistoia, Italy) of the University of Florence, as shown inFigure 4, based on the commercial anthropomorphic manipulator Comau Smart Six and a custom IMU designed by ECM Spa. The Figure 3 shows the HIL test rig architecture: a Windows^{TM} host, thanks to Matlab-Simulink^{TM}, provides the implementation of the DM, CWA and CLIK systems. The C4GOpen, composed of a RTAI- Linux host and the standard C4G Control Unit, allows to respect the strict timing constraints for the tracking of the trajectories, overcoming the typical constraints of robot controller closure. The implementation of the open controller is performed through the software suite Orchestra Control Engine by Sintesi^{TM}.

4. Results

The testing procedure has been applied to five worst-case-design paths, whose features are summarized in Table 1. Every path is composed of three phases of traction and braking, affected by degraded adhesion and interspersed by a phase of coasting. As concerns the adhesion, sections characterized by good adhesion conditions (static adhesion coefficient, μ=0.3) alternate sections under degraded adhesion conditions (μ=0.1). The five paths are considered worst-case, since the changes of slopes and the curves are faced at a such low speed that the angular rates are comparable to the noise of the gyroscope.

Table 1: features of the testing paths

ID	Features
1	Articulated altimetry, with uphills (downhills) up to 3 %, without any curves
2	Combination of curves (radius of curvature of 1800 m) and slopes (uphills and downhills up to 3 %)
3	Curves (radius of curvature of 1800 m) and uphills (downhills) with mixed slopes (1, 2, 3 %)
4	Very long (nearly 30 km) with slopes in the coasting phase, too
5	The first uphill, with slope of 3 %, is faced at a speed of about 15 km/h

In Table 2 it is possible to evaluate the improvements of the innovative system of adhesion detection compared to the SCMT solution. For each path, in the first column, the true percentage of path interested by degraded adhesion is reported. In the second and third column, the estimated values of degraded adhesion condition are shown and the respective error compared to the true value.

Table 2: comparison between the wheel-rail adhesion detection performance

ID	% true degraded adh.	% SCMT degraded adh.	% INS-ODO degraded adh.	SCMT error	INS-ODO error
1	40.53	61.14	44.15	20.61	3.62
2	40.47	57.23	43.39	16.76	2.92
3	35.21	52.40	38.10	17.19	2.89
4	30.28	43.19	32.05	12.91	1.77
5	39.65	61.85	44.00	22.20	4.35

Figure 5 and Figure 6 evidence, for the path #1, that the algorithm performances are good, since the speed and the position estimation errors are much smaller than the ERTMS requirement thresholds.

Same good results can be found for the other paths, too.

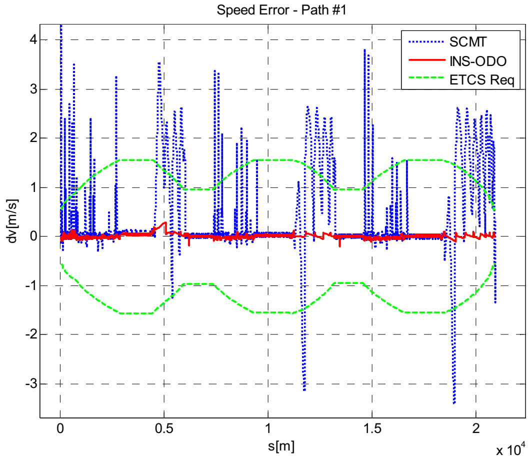

Figure 5: speed error w.r.t. ERTMS requirements

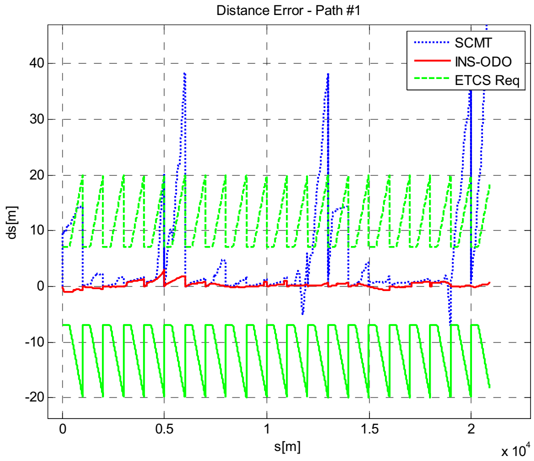

Figure 6: distance error w.r.t. ERTMS requirements

Conclusions and Acknowledgments

The aim of this work has been the development of an innovative localization algorithm for railway vehicles which could enhance the performances, in terms of speed and position estimation accuracy, of the classical odometry algorithms, such as the Italian SCMT. The performances are strictly related to a reliable detection of degraded adhesion conditions. In this paper an innovative method, based on a real-time estimation of the track-gradient, is implemented and tested through a HIL dynamic simulator, composed of an anthropomorphic robot and a custom IMU. The enhancement in the detection of degraded adhesion conditions takes advantages to the odometry algorithm performances in terms of estimation accuracy and reliability, even in HS lines, since the elaboration of the information occurs at a frequency suitable to detect quickly - less than a ten of meters - the state of the adhesion condition.

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