Odometric Estimation for Automatic Train Protection and Control Systems

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Abstract

The paper summarizes the main steps necessary for the definition of the odometry algorithm that can be used in the Automatic Train Protection and Control Systems. In this kind of devices the availability of a reliable speed and travelled distance estimation is essential for the efficiency and the safety of the whole system. The first step is the analysis and the choice of the sensors that can be used for the odometric estimation, a procedure that fuses the measures obtained from the sensor is defined. In the paper the main features of the developed solution will be summarized and its performance, in terms of precision in the speed and travelled distance estimation will be presented.

Introduction

The increasing operational speeds and network capacity in modern railways require automatic systems that allow to control the traffic on the lines. The traditional signaling systems are no more sufficient to guarantee the required safety and efficiency to the railway networks. Automatic Train Protection (ATP) systems give to the driver information on actual speed, distances to points where speed restrictions are present (objective points), the permitted speed (the speed that would allow to reach the objectives with the required speed). If the actual speed overcomes this speed value the system alerts the driver by means of visual and acoustic warnings. If the driver action is not sufficient the system automatically cuts the traction torque (if it is present) and then activates the braking procedure.

Safety and efficiency of an ATP are strictly related to the reliability of train position and speed estimation on the line. Such estimates are regularly computed by odometric subsystem, using a set of data received from several sensors. For this estimation safety is generally more important than accuracy[1,...,7]. The aim of the work described in this paper is to increase the operational safety of automatic train protection systems (for example ERTMS, the system that is being adopted in the high speed lines in Europe) by a clever fusion of data provided from sensors.

The described algorithms "fuses" the information from different types of sensors, since this can improve significantly both performance (the system has more data usable to detect the state of the environment in which it operates) and safety (the probability of failures decreases) of the estimation. The sensors chosen for the estimation are two encoders which measure the angular speed of two axles and a longitudinal accelerometer positioned on the coach body. The system uses also data from the track, that are communicated to the train when it passes on fixed points on the line (balises). When the train meets a balise, the position information is reset and the information on line slope in the following part of the line is given to the on board system.

The authors have worked in the design of the odometry algorithm for the Italian ATP system, named SCMT (Sistema di Controllo Marcia Treno), based on the measure of two wheel angular speeds. For this system different algorithms were analyzed and compared (for example based on fuzzy logic and neural networks)[8,...,11]. The solution that was agreed by the railway companies and then implemented in the system was based essentially on heuristic considerations, because it leaded to higher integrity and safety targets. This algorithm has been considered as the starting point of a new system, its limits have been analyzed and corrected adding different types of sensors.

Generally speaking, the ability of one isolated sensor to provide accurate reliable data is limited as the environment is usually not very well defined. Furthermore the environmental condition may vary during train operations, and each sensor has a limited range in which it has optimal performance. In the specific application, wheel angular speed sensors give a reliable and accurate estimation of train speed when the adhesion conditions between the wheel and the rail are good, while in presence of wheel sliding (during a traction or a braking phase) the estimation error can be high.

Sensor fusion techniques seek to overcome the drawbacks of sensors by combining information from independent sources of limited accuracy and reliability in order to extract better information in terms of accuracy and reliability. Furthermore the use of different sensors reduces the system vulnerability to failures of a single component and can provide more accurate information [12,...15].
Measured data can be combined (fused) in a variety of levels, from the raw data level to a state (vector) level. The fusion could be performed by means of multiple process models, that allow a modular approach in the estimation process. The designer specifies a set of models, each model elaborates the measured data in a different way and gives an output value. Each process model output can be considered as the measure performed by a virtual sensor. At any given time each model has a certain degree of uncertainties, a procedure that fuses the outputs from the multiple process model has then to be defined.

Different sensor types have been analyzed and compared for the odometric estimation, the criteria adopted for the choice are essentially the reliability, the precision, the robustness. The configuration that optimize the compromise between the complexity of the system and the precision in the estimation is composed of two wheel angular speed sensors and a mono-axial accelerometer.

In the paper the features of different types of sensors are presented, including the optimal conditions in which they can operate and their drawbacks and limits. Then a possible solution for the sensor fusion is briefly described.

The procedure has been designed, trained and validated using a wide set of experimental and simulated data. Experimental data are useful to calculate the global performances, in terms of estimation precision, while simulated tests can be used to verify the behavior in particularly critical conditions (that are difficult to be reproduced experimentally but cannot be a priori neglected), for example extremely degraded wheel rail adhesion conditions, locked axles, failure of onboard subsystems etc..

A particular attention is devoted to the choice of the tests used to develop and validate the estimation procedure, since the input data set has to represent all the real conditions that it will meet in normal conditions. The criteria used to define the test set should allow to obtain a compromise between its dimension (number of tests) and the complete reproduction of all the possible cases. The parameters that mainly influence the algorithm precision were identified from the analysis of the sensor characteristics. For example, wheel angular speed sensor precision is strictly related to the wheel/rail adhesion, the type of train, the type of operation, while the accelerometer performance is influenced by the line gradient. For each parameter a series of classes have been defined and combined in order to obtain a set of tests able to represent the behavior of the algorithm in all the cases it could meet in the reality and then to obtain a reliable estimation of its performance.

Sensors

Different types of sensors can be used in the odometric subsystem. In this section the sensors used to perform the preliminary tests are briefly described. Three types of sensors have been tested by means of experimental activities and numerical simulations: wheel angular speed sensors, radar Doppler speed sensors and mono-axial accelerometers.

Wheel angular speed sensors

Wheel angular speed sensors are frequently used to perform odometric estimations due to their robustness and reliability (they are used for example by the wheel slide protection and anti-skid systems). From the wheel angular speed sensor measure the wheel peripheral speed can be directly calculated. If the wheel is not sliding this is a good and reliable estimation of the train speed, in this case the precision of the estimation is essentially related to the reliability of the information on the wheel diameter. If two angular speed sensors are used specific procedures that allows to compensate eventual errors on the diameter information can be defined. However, 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 sliding arises. If the train is accelerating the wheel peripheral speed tends to overcome the train speed, while in a braking phase the wheel peripheral speed is lower than the train one. The dynamics of the wheels during the sliding depends significantly on the mechanic feature of the vehicle (masses and inertia, geometric properties, suspension characteristics etc.) and on the interaction between the different on board subsystems, in particular (braking system and WSP, Wheel Slide Protection, traction system and anti-skid).

The sensor output is a signal proportional to the impulse counter $c_i$, the wheel angular speed $\omega$ can be evaluated by finite derivatives as follows:

$$\omega = 2\pi/N(c_i - c_{i-1})/\Delta T,$$

where $c_i$ is the current sample, $c_{i-1}$ is the preceding sample, $N$ is the number of impulse per revolution and $\Delta T$ is the sampling time.
**Radar Doppler**

Radar Doppler sensors measure the relative speed between the body on which they are located and the surface on which they point detecting the frequency shift between the transmitted and the reflected signal [16,17]. The reliability of the measure depends on different parameters and can be affected by non negligible errors, for example an extremely smooth surface may cause offsets and systematic error in the measure, it is furthermore influenced by the vehicle pitch motion, vibrations etc.

![Figure 1: example of experimental test run, wheel speed and train speed measured by a radar Doppler sensor](image)

**Mono axial accelerometers**

In the odometric evaluation often a measure of the train longitudinal acceleration can be useful to recognize particular operative conditions, for example wheel adhesion losses and slidings. The acceleration measure could also be used to estimate by numerical integration train speed and travelled distance when the reliability of the other sensors is low. The accelerometer that could be used for this task should have a quite low bandwidth (about 2-3 Hz), should be able to measure continuous accelerations, should be robust and should not be sensitive to the acceleration component in the other directions (vertical and lateral). The selected accelerometer is a closed loop transducer that uses as sensitive element a pendulum. When the sensor is submitted to an acceleration, the pendulum mass tends to move in the direction opposite to the acceleration, due to the inertia forces. Its position is detected and converted into a current that is fed back to bring it back to its initial position. The accelerometer then measures the inertial forces that arise when the train is subject to an acceleration. But if the sensor sensible axle is not perfectly horizontal, it also measures the component of the gravity acceleration along that axle. In other terms, the sensor also behave as an inclinometer: if the structure on which the sensor is mounted is subject to a longitudinal acceleration \(a\) but is rotated with an angular misalignment \(\varphi_d\) with respect to an horizontal axis perpendicular to the sensitive direction the sensor will measure the following acceleration offset value:

\[
a_m = a + g \sin \varphi_d.\tag{2}
\]

Moreover, it can be verified that if the sensor is mounted with a horizontal angular misalignment \(\zeta\) between the sensitive axis and the longitudinal direction, the measure is affected by a multiplicative error proportional to the cosine of \(\zeta\), in other terms the corresponding measured acceleration is:

\[
a_m = \cos \zeta (a + g \sin \varphi_d).\tag{3}
\]

The sensor has been analyzed with a set of laboratory tests that allowed to analyze the effect of misalignments in the different directions and its dynamical behavior. The transfer function between the input acceleration and the measured signal is the following:

\[
c_m(s) = \frac{\frac{1}{s}}{\left(\frac{5}{s+5} + \frac{5}{s+5}\right)}\(s+5\) + 1.\tag{4}
\]
The following figures show the effect of the misalignment in the measure error and the sensor transfer function.

![Figure 2: a) accelerometer measure error as a function of the angular misalignment $\zeta$ and $\eta$, b) accelerometer transfer function magnitude.](image)

The odometry algorithm

The following block diagram shows the structure of the algorithm used to estimate train speed and travelled distance.

![Figure 3: odometry algorithm block diagram](image)

In the **Data Acquisition and Conditioning** block the measures from the different sensors are collected and elaborated: the wheel velocities are calculated by means of numerical derivatives starting from the impulse counters.

The wheel speeds are then elaborated by derivative filters in order to obtain an estimation of wheel acceleration. In the implementation described in this paper simple first order low pass filters were used to smooth the effect of measure noise in the wheel acceleration estimations. Some tests were made using adaptive filters as those described in [18] and Kalman filters [19,20]. Future versions of the algorithm will include this type of elaborations, that allow to improve the reliability of the acceleration estimation.

The accelerometer measure is corrected taking into account the information of the line gradient available from the on track subsystem:
It is then evident that the reliability of the corrected acceleration $a_{mc}$ is strictly related to the reliability of the information of the line gradient $\varphi_{d,est}$.

In the **State Variable Evaluation** subsystem some variables are defined in order to identify the state in which the system is, and to choose the proper strategy to perform the speed evaluation. In this phase the number of sensors that can be used for the estimation is firstly evaluated. A sensor is excluded from the estimation if it is affected by a failure or if, due to the particular measure condition, it cannot be considered reliable (for example if during a braking the wheel on which the sensor is located is locked due to the low adhesion level).

Then the adhesion conditions are evaluated by means of a tachometric and an accelerometric criterion. The tachometric criterion states that the wheels are sliding or skidding if the absolute value of the difference between the wheel peripheral speeds overcomes a fixed threshold. The accelerometric criterion compares the wheel accelerations with the accelerometer measure: a wheel is sliding if the absolute value of the difference between its acceleration and those measured by the accelerometer overcomes a fixed threshold.

In other terms, the logical variables $s_1$ and $s_2$ ($s_k = 1$, $k=1,2$ if the wheel $k$ is sliding) are defined as follows:

$$s_k = (\text{abs}(v_1 - v_2) > \Delta v_s \text{ or abs}(a_1 - a_{mc}) > \Delta a_s)$$  \hspace{1cm} (6)

The evaluation of the driving conditions (braking/traction) is performed observing the acceleration measured by the accelerometer. The logical state variable $t_{op}$ ($t_{op} = 0$ in a braking phase, $t_{op} = 1$ in a traction phase) is thus defined as follows:

$$t_{op} = (a_m > a_r)$$  \hspace{1cm} (7)

where $a_r$ is a fixed threshold that takes into account the motion resistances. It can be observed that in this case the non compensated acceleration is used, since this measure implicitly takes into account the effect of the line gradient.

Further state variables are calculated combining the preceding ones and elaborating the sensor measures; the state of the system is represented by other integer, logical and real variables (approximately 40) that allows to identify specific conditions (sensor failures, recovery of adhesion, wheel locking etc.)

In the train **Speed and Travelled Distance Estimation** block, starting from the state evaluation the proper strategy for the evaluation of the speed is chosen and performed. For example, if the adhesion conditions are estimated good the train speed can be evaluated directly from the wheel peripheral speed:

$$v_i = \max(v_{1i}, v_{2i})$$  \hspace{1cm} (8)

If the wheels are sliding and the train is accelerating the speed is evaluated as the minimum between the wheel speeds and a value obtained integrating an estimation of train acceleration:

$$v_i = \min(v_{1i}, v_{2i}, v_{i-1} + a_{est} \Delta T)$$  \hspace{1cm} (9)

The acceleration estimation $a_{est}$ is calculated as a function of the acceleration value measured by the accelerometer and the mean between the wheel accelerations:

$$a_{est} = \max(\min((a_1+a_2)/2, a_m+\Delta a), a_m-\Delta a)$$  \hspace{1cm} (10)

If the wheels are sliding and the train is braking the speed is evaluated as the maximum between the wheel speeds and a value obtained integrating an estimation of train deceleration:

$$v_i = \max(v_{1i}, v_{2i}, v_{i-1} - d_{est} \Delta T)$$  \hspace{1cm} (11)

The deceleration estimation $d_{est}$ is calculated as a function of the acceleration value measured by the accelerometer and the mean between the wheel accelerations:
\[ d_{\text{est}} = \max(\min(-(a_1+a_2)/2,-a_n+\Delta d), -a_n-\Delta d) \]  

(12)

When the system recognizes the begin of a sliding during a braking starting from an initial adhesion phase the estimated speed remains constant for a time interval whose amplitude depends on the speed. This allows to compensate eventual delays in the recognition of the sliding due to the effect of filters. The following figures show some examples of train speed reconstruction.

The travelled distance is evaluated as the numerical integration of the estimated speed:

\[ s_i = s_{i-1} + v_i \cdot \Delta T \]  

(13)

The travelled distance estimation is reset when the train passes on a reference balise.

![Figure 4: example of train speed estimation performed by the developed algorithm, a) estimation during a traction phase, b) estimation during a braking.](image)

**Testing**

The algorithm was developed and tested using a wide set of simulated data obtained from tests with various train configurations (single vehicles and entire trains). Experimental test runs were also used to analyze the performance of the developed algorithms, in the tests train speed was measured using an optical sensor, while wheel angular speeds were measured using encoders. Most of the available tests are relative to braking and traction tests conducted with artificially degraded adhesion conditions (the degradation was obtained by spraying a solution of water and soap on the rail, as usual in test runs for the certification of wheel slip protection systems). The tests conducted using an entire train (traction and braking tests) were characterized by a maximum speed of 70m/s. The gradient on the line where the test runs were conducted was nearly zero. In each test eight axles speeds were measured.

Various particular conditions (which cannot be easily reproduced by means of test runs) were also simulated, in order to test the safety and the reliability of the algorithms, for example:

(a) simulation of one axle locking up;
(b) simulation of two axles locking up;
(c) simulation of one damaged speed sensor;
(d) simulation of two damaged speed sensors on the same axle (in this situation the information relative to that axle is not available);
(e) simulation of two damaged speed sensors on two different axles;
(f) erroneous line gradient information;
(g) jitter error on counter values;
(h) accelerometer misalignments;
(i) reliability of the line gradient information.

The simulated tests were carried out with a software simulator developed by the authors to control an Hardware In the Loop test rig for the development and type approval of WSP systems [21][22]. The
simulator is able to reproduce the longitudinal dynamics of a generic train, also in presence of low adhesion conditions. The behavior of the many on board subsystem (including WSP and anti-slip devices, braking and traction system etc) can be modeled. The simulator calculates during a generic test all the kinematic variables of the train, from these information the measure of the sensors can be simulated (including their systematic errors, their bandwidth, errors due to the discretization and quantization of the signal, failures, etc.). The results of the testing were compared with the ERTMS specification requirements described in [23,..,26] and summarized in the following figures.

![Graph](image1.png)

Figure 5: ERTMS specifications on odometry error: a) error on the travelled distance, b) errors on the estimated speed.

Results

The results of a first series of tests showed that the algorithm performance had a significant dependence on the reliability of the line gradient. In other terms, the performance were optimal if the information on the line gradient is correct, but highly decreased when it is inaccurate or absent. In order to improve the robustness of the algorithm with respect to errors on the line gradient information the value of the acceleration thresholds used by the algorithm for the evaluation of the state variables were modified and defined as a function of the gradient reliability ($\Delta a$, $\Delta d$, $\Delta a_l$ etc.). The tests showed also a negligible sensitivity of the algorithm performance with respect to accelerometer misalignments.

The following figure shows as an example the estimated speed during a part of an experimental test. Figure 6 a) shows the measured peripheral speeds, the reference train speed (measured in this case with an optical sensor) and the odometric estimations. Three speed reconstruction are represented in the figure: the first one is obtained with the developed algorithm without the compensation of the line gradient inaccuracy, the second one is obtained with the SCMT algorithm, the third one is obtained with the proposed algorithm, taking into account the inaccuracy of the gradient information. Figure 6 b) shows the error in the train speed estimation obtained with the different versions of the odometry algorithms, compared with the limits proposed in the references [23,..,26]. The shown results are relative to a test in which the wheel/rail adhesion was artificially degraded and severe wheel slidings (up to 5 m/s) are evident during the traction and braking phases. Figure 7 shows the error on the travelled distance estimation, considering a balise reset for each 1000 m, compared with the limits proposed in the references [23,..,26]. As it can be seen, the proposed algorithm, with and without the line gradient inaccuracy compensation, give a better estimation of train speed with respect to the SCMT algorithm. The integration of the accelerometer in the odometry system then leads to a significant improvement in the precision of the estimation.
Figure 6: example of train speed estimation a) train speed, wheel peripheral speeds, estimated speeds, b) errors in the speed estimation

Figure 7: error on travelled distance estimation.

Figure 8 and 9 summarize the results obtained with the simulated tests. As previously described, the numerical simulations include extremely severe conditions, that are difficult to be reproduced in the reality but are cannot a priori be neglected. Figure 8 shows the standard deviation of the error on the speed estimation for each test, obtained with the proposed procedure (with and without the line gradient compensation) and the SCMT algorithm. In almost all the tests the proposed procedure allows to significantly reduce the speed error distribution amplitude. Figure 9 shows for each test the ratio between the number of samples in which the requirement on speed error is not complied and the total number of samples. Also from this diagram the improvement of the performance obtained adding the longitudinal acceleration measure is evident. The results relative to the simulated tests are summarized in Table 1.
Table 1: relative speed error, results for the simulated tests.

<table>
<thead>
<tr>
<th></th>
<th>ERTMS (optimal conditions)</th>
<th>ERTMS with gradient compensation</th>
<th>SCMT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative speed error, mean</td>
<td>0.0015</td>
<td>0.0019</td>
<td>0.0053</td>
</tr>
<tr>
<td>Relative speed error, standard deviation</td>
<td>0.0066</td>
<td>0.0085</td>
<td>0.0138</td>
</tr>
<tr>
<td>Ratio between the samples that do not respect the ERTMS error limits and the total number of samples</td>
<td>0.0099</td>
<td>0.0182</td>
<td>0.0438</td>
</tr>
</tbody>
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Figure 8: Simulated tests, standard deviation of the error on the travelled speed estimation.

Figure 9: simulated tests, ratio between the samples that do not respect the ERTMS limits on the speed estimation and the total number of samples.

Conclusions

The paper summarizes the main features of an odometry algorithm for ATP/ATC systems. The algorithm fuses the measures obtained from two angular speed sensors located on two independent wheels and a monoaxial accelerometer used to estimate the longitudinal train acceleration. The features of the sensors and the conditions in which their estimate could have a low reliability are described, then a procedure for the sensor fusion is proposed and described. The performance of the algorithm are then evaluated with a series of tests obtained from experimental train runs and
simulated scenarios. The performance were compared with those obtained with the algorithm developed for the SCMT system (the Italian ATP system), that uses the information from only two angular speed sensors placed on two independent axles. The results shows a sensitive increasing in the estimation precision both for the speed and for the travelled distance estimation. The performance of the proposed algorithm could be furthermore improved using more advanced techniques for the elaboration of the measured data (some preliminary tests have been conducted with adaptive and Kalman filters) and different estimation procedures (based for example on recurrent neural networks).

References


[24] EEIG ERTMS Users Group, “Performance Requirements for STMs”, Reference EEIG Subset-059, Issue 0.0.6, 28/03/00.

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