Train Position and Speed Estimation by Integration of Odometers and IMUs

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Abstract

The paper summarizes the main features of an odometry algorithm to be used in modern Automatic Train Protection and Control (ATP/ATC) systems. The availability of a reliable speed and travelled distance estimation is fundamental for the efficiency and the safety of the whole system. The integration of odometers and an IMU (Inertial Measurement Unit) in the position and speed estimation process was investigated. The objective is to increase the accuracy of the odometric estimation, especially in critical adhesion conditions. The preliminary results show a significant improvement of position and speed estimation performance. Accurate train navigation systems which scarcely rely of information coming from the infrastructure will open a roadmap for the development of a more and more effective and efficient exploitation of rail stock and infrastructure.

The paper presents the criteria to fuse the information from the different sensors. Then a set of test results showing the improvement of the estimation process are presented and discussed.

I - Introduction

Reliable estimation of speed and distance by dead reckoning and/or absolute navigation is the base of a safe and efficient Automatic Train Protection system (ATP). ATPs are used to safely increase the infrastructure capacity, by maintaining the safety of operation. The importance of such monitoring and control systems is continuously increasing.

Dead reckoning relies on sensors: typically wheel angular speed sensors, radar Doppler sensors, accelerometers, gyroscopes, etc. [1,6,7]. The reliability of dead reckoning is related to operative conditions [1-4] in which the sensors operate. Generally one isolated sensor can partially provide accurate data, its reliability ranges are often limited, while the environment is usually not very well defined. Furthermore the environmental condition may vary during train operations, often in an unpredictable and unquantifiable way. For instance, wheel angular speed sensors, commonly used to estimate train speed, give a reliable and accurate estimation of train speed but only when the adhesion conditions between the wheel and the rail are good. In presence of wheel sliding (when train is accelerating or braking) the estimation error can be very high. Sensor fusion techniques allow limiting the drawbacks of single sensors by combining information from independent sources (each characterized by limited accuracy and reliability) in order to extract better information. Furthermore data fusion techniques are able to reduce system vulnerability to failures of single components and can definitely provide more accurate information. Methods for the sensor data fusion are widely described in the literature, some references on this topic can be found for example in [14-17].

This study builds on a previous analysis of an odometric algorithm based on two angular speed sensors located on two independent wheels [10-13]. This solution is sensitive to wheel/rail adhesion and may fail in presence of slip/sliding, due to traction or braking actions. The analysis of the methods described in [6,7] suggested that an accurate measure of longitudinal acceleration can significantly improve the recognition of such degraded adhesion conditions and could be used to estimate train speed and position when wheel speed sensors fail due to slide and slip phenomena. A mono-axial accelerometer can be used to measure longitudinal acceleration, but the measure is affected by systematic errors, due to sensitivity to car body angular displacement [6,7] (mainly due to track gradient).

An estimation of train longitudinal acceleration less sensitive with respect to sensor angular displacements can be obtained by combining accelerometers and gyroscopes [2], furthermore the use of different types of sensors, whose information are properly weighted according to specific operative conditions, may significantly describe increase the algorithm reliability [3].

In the paper, the integration of odometers and an IMU (Inertial Measurement Unit) in the position and
speed estimation process is described. The objective is to increase the accuracy of the odometric estimation, especially in critical adhesion conditions. The preliminary results show a significant improvement of position and speed estimation performance. The paper presents the criteria to fuse the information from the different sensors. Then a set of test results showing the improvement of the estimation process will be presented and discussed. Accurate train navigation systems which scarcely rely on information coming from the infrastructure will open a roadmap for the development of a more and more effective and efficient exploitation of rail stock and infrastructure.

II - Sensors for the odometric estimation

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 (Tachometer)
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 compensating 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 \( c \), the wheel angular speed \( \omega \) can be evaluated by finite derivatives as follows:

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

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.

Accelerometers
An accelerometer is a device that can measure acceleration generated by the movement of an object along an axis. This instrument sensitive to all external forces acting upon it, including gravity and centrifugal forces. Accelerometers could have some different mechanism to transduce external force: most common are mechanical accelerometer (essentially a spring-mass-damper system), piezoelectric accelerometers (bases on a property exhibited by certain crystals, across which a voltage is generated when they are stressed), and capacitive accelerometers (sense a change in electrical capacitance, with respect to acceleration).

Modern accelerometers are often small Micro Electro-Mechanical Systems (MEMS), consisting of a cantilever beam with a proof mass (also known as seismic mass). Damping results from the residual gas sealed in the device. Under the influence of external accelerations the proof mass bends from its neutral position. This deflection could be measured in different ways. Most commonly, the capacitance between a set of fixed beams attached to the proof mass is measured. An alternative is to integrate piezoresistors in the springs to detect spring deformation, and thus deflection. Another, far less common, type of MEMS-based accelerometer contains a small heater at the bottom of a very small dome, which heats the air inside the dome to cause it to rise. A thermocouple on the dome determines where the heated air reaches the dome and the deflection off the center is a measure of the acceleration applied to the sensor.

There are some important parameters that influence accelerometer performance: first one must choose between an accelerometer with analog output or digital output. Then there is number of axis
and measurement range. Then we have sensitivity and bandwidth: sensitivity is the ratio of the output voltage to the sensor parameter of interest. Bandwidth is the frequency we use to measure changes in acceleration. Noise characteristics of these devices are also very important. Voltage noise changes with inverse square root of the bandwidth. Faster we have to read accelerometer changes (vibration in compare with car driving), worse accuracy we get. For the modeling of sensor error sources refer to [29].

**Gyrosopes**

Gyrosopes measure changes in vehicle orientation and by means of the inertial properties of a wheel or rotor spinning at high speed.

Mechanical gyroscopes are composed of a axis free to spin along a direction and, thanks to the conservation angular momentum principle, it can maintain its orientation. Angular rates in correspondence of rotations of the platform where gyroscope is mounted are measured respect of the fixed spin axis.

Gyrosopes based on other operating principles also exist, such as solid-state ring lasers (RLG), fibre optic gyroscopes (FOG) that relies on Sagnac Effect and the extremely sensitive quantum gyroscope. Most of modern gyroscopes are the cheapest and smallest MEMS, based on vibrating mechanical elements to sense rotation. Vibratory gyroscopes rely on the transfer of energy between vibratory modes based on Coriolis acceleration. As the MEMS accelerometers, MEMS gyroscopes have low-power consumption requirements, are very small and cheap, so they are quickly replacing mechanical and optical sensors. The same are the important parameters that influence performances: analog/digital, number of axis, measurement range, sensitivity, bandwidth and noise. For the modeling of sensor error sources refer to [29].

**Magnetometers**

A magnetometer is a scientific instrument used to measure the strength and/or direction of the magnetic field in the proximity of the instrument and, in absence of local magnetism, it can detect Earth's magnetic field.

There are several types of electronic compasses to chose: fluxgate, magneto-resistive, magneto-inductive. The fluxgate sensor consists of a set of coils around a core with excitation circuitry that is able to measure magnetic fields; Anisotropic Magneto-Resistive (AMR) sensors have a sensing element that is made from a nickel-iron alloy (or Permalloy). The electrical resistance of the Permalloy sensing element changes in presence of magnetic fields.

Magnetometers can be used as heading sensor, where heading is the angle formed between the longitudinal axis of the sensor and the direction to the true North Pole. The key to accurately finding a compass heading is a two-step process: 1) determine the horizontal components of the earth's magnetic field and 2) add or subtract the proper declination angle o correct for true north. (the difference between magnetic north and true north is well known with location and is called *magnetic declination*). For first practice it's important to compensate the dip angle (magnetic inclination) because magnetic field will point partially downwards (northern hemisphere) or upwards (southern hemisphere). Another good practice is the compensation for nearby ferrous effects. Magnetic distortions can be categorized as two types—hard iron and soft iron effects. Hard iron distortions will remain constant and in a fixed location relative to the compass for all heading orientations. The soft iron distortion arises from the interaction of the earth's magnetic field and any magnetically soft material surrounding the compass. For the modeling of sensor error sources refer to [30].

**GPS**

GPS is the acronym for Global Positioning System and is a technology for location estimation. The system is based on received radio signals transmitted by satellites orbiting the Earth. The estimation provided is a three-dimensional position in absolute coordinates with accuracy of 10-20 m for standard implementations and 1-2 m for enhanced GPS such as Wide-Area Augmentation System (WAAS). The most widely accepted system is base on NAVSTAR satellite, deployed and maintained by the United States Army. The Russian government operates a similar system, named GLONASS, and another alternative is being deployed by the European Union, named Galileo.

GPS can guarantee absolute and drift-free position estimation but it can fail due to inaccessibility of a satellite signal in particular situations. Moreover GPS data frequency is lower (1-10 Hz) than on-board-sensor frequency (10-100 Hz). So GPS is not able to meet the basic requirements of integrity and availability and the vehicle can't be equipped only by a satellite receiver but also by inertial navigation sensor.
Ill - Odometry based on Tachometers

The present study builds on the previously developed SCMT odometry algorithm [10,13], which was based on the measures from two wheel angular speed sensors. Actually this solution was simple, robust and cheap, since the adopted sensors are widely diffused in railway applications. On the other hand, its weak point was the low reliability in presence of degraded adhesion condition, which is rather common in railway practice. Other types of sensors were considered, for example Radar Doppler sensor, that however presented a lower robustness and its output is often affected by noise and systematic errors [18,19].

In some previous works [7,8] the performances obtained with different approaches in the definition of the sensor fusion algorithm are compared. The analyzed algorithms can be substantially divided into two main types: data-driven algorithms (such as neural networks) and model-driven algorithms. Due to the drawbacks of a data-driven algorithm (they are developed on the basis of a series of input/output pairs, that have to span the whole operative space of the algorithm, a physical interpretation of the algorithm parameters is not suitable, and the sensitivity of the results on such parameter variations is a priori difficult), a model driven solution has been chosen.

On the other hand, model-driven estimation procedures are based on the physical interpretation of the sensor measure. In the presented estimation problem, a dynamic model of the measure system can be efficiently defined due to the high number of variables that can affect the sensor outputs; so the estimation procedure is based on some heuristic criteria defined on the observation of a wide set of experimental data. The resulting procedure, whose main features are described in the following, depends on a set of parameters that represent physical entities (such as acceleration thresholds, time window lengths, filter bandwidth, etc.).

The following main steps can summarize the algorithm:

- Data acquisition and conditioning;
- State variable elaboration;
- Train speed and travelled distance evaluation

Data acquisition and conditioning

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 directly starting from the impulse counters, then an estimation of wheel acceleration is provided.

State variable evaluation

In the state variable evaluation subsystem, a set of variables are defined in order to identify the state of the system (not sliding, high or low sliding, etc.), and to choose the proper strategy to perform the speed evaluation. The criteria described in this section for the definition of state variables was substantially derived from the analysis of the dynamical behaviour of wheel speeds and accelerations observed during experimental tests [8,9]. The adhesion conditions are evaluated by means of both a tachometric and an accelerometric criterion.

- The tachometric criterion states that two wheels (or least one of them) are sliding or skidding if the absolute value of the difference between their wheel peripheral speeds overcomes a fixed threshold.
- The accelerometric criterion compares the wheel peripheral accelerations: a wheel is sliding if the absolute value of its acceleration overcomes a fixed threshold.

Further state variables are calculated combining and elaborating the sensor measures. The state of the system is represented by other integer, logical and real variables (approximately 40) that allow identifying a wide number of specific conditions (sensor failures, recover of adhesion, wheel locking, etc.).

Evaluation of train speed and travelled distance

In the train speed and travelled distance estimation block, the proper strategy for the evaluation of the speed is chosen and performed starting from the state evaluation. For example, if the adhesion conditions are estimated ‘good’, the train speed can be evaluated directly from the peripheral speeds of the wheels, when the wheels are sliding and the train is accelerating, the speed is evaluated as the minimum between the speeds of the two wheels and a ‘reference’ value obtained by integrating the estimated train acceleration, if the wheels are sliding and the train is braking, the speed is evaluated as the maximum value between the two wheel peripheral speeds and the velocity value obtained by integrating the estimated train deceleration.
IV - The inertial navigation algorithm

The outputs of IMUs (triaxial accelerometers and triaxial gyroscopes) can be processed to determine position, velocity and attitude of a vehicle through navigation algorithms called INS. We define two reference frames: Navigation frame with axis fixed respect to East, North and Up directions and Body frame with axis aligned with the vehicle. The rotation matrix $R_{n}^{b}$ (updated from gyroscope measurements) expresses the relationship between navigation and body frame and it's used to transform the acceleration measurements to the navigation frame. It is then possible to estimate the velocity of the vehicle through an integration of the transformed acceleration and the position in fixed reference through a double integration.

Mechanization Equations \([29]\) describe the discretized equations of motion and consist of four steps:
1) Known error compensation of raw inertial data (deterministic correction of bias, scale factor, non-orthogonality);
2) Attitude Update (for example quaternion updating through gyroscope measurements):
\[
q_{t+1} = q_{t} + \frac{1}{2} \Omega(\omega_{t}) \cdot q \cdot dt
\]  
(2)
3) Transformation of specific forces from body ($f_{b}$) to navigation frame ($f_{n}$) and gravity compensation
\[
f_{n}^{a} = R_{n}^{b} \cdot f_{b} + g
\]  
(3)
4) Velocity($v$)/Position($r$) Integration
\[
v_{t+1}^{n} = v_{t}^{n} + f_{n}^{a} \cdot dt
\]  
\[
r_{t+1}^{n} = r_{t}^{n} + v_{t}^{n} \cdot dt
\]  
(4)
Mechanization Equations blindly process the raw inertial data that contain errors (e.g. for gyroscope and e_{a} for accelerometer) and, due to time integration performed, introduce error in attitude ($\delta \Phi$), velocity ($\delta v$) and position ($\delta r$) according to:
\[
\delta \Phi \approx e_{g} \cdot t \\
\delta v \approx e_{a} \cdot t + \frac{1}{2} e_{g} \cdot t^{2} \\
\delta r \approx \frac{1}{2} e_{a} \cdot t^{2} + \frac{1}{6} e_{g} \cdot t^{3}
\]  
(5)
Deterministic compensation is not enough to erase the error due to random white noise. Stochastic filters such as Extended Kalman Filter can be able to improve performances of estimation of INS algorithms. EKF equations for inertial navigation are described in \([31]\) and consist of the state transition and the observation model.

Stochastic filter reduces the integration error, but cannot provide the high accuracy needed. In these cases higher quality information can be achieved using multiple sensor and integrate them. There are different methods of data fusion that have been developed for different types of sensors and applications. Kalman filtering has more potential for integration of navigation sensors, where the differences of two sets of sensor data are used as observations.

![Figure 1: Integration of two navigation sensors using Kalman filtering](image)

The filter is based on the system error model and the state vector of this model includes errors that may affect the navigation accuracy.

Redundant sensor could be magnetometer, angular speed sensors and GPS, which could correct respectively attitude estimation, velocity estimation and position estimation. It must emphasized that
these three sensors are not always available: magnetometer may be disabled when distortions are large and not-systematic; angular speed sensors, in case of slide/slip, cannot guarantee exact measurement of speed; GPS can fail due to inaccessibility of satellite signals.

V - An odometry algorithm based on GIT and INS

Taking into account of Odometry algorithm described in Chapter III and INS strategies showed in Chapter IV, an innovative cooperative odometric algorithms based on one tachometer mounted on the third axle and a IMU have been developed.

The main suggestion of the algorithm is that inertial sensors process a velocity estimation that is corrected by tachometer when the adherence condition is good. This strategy has been defined with the assumption of the train motion as one dimensional motion: in fact trains follow a fixed trajectory and the position is expressed in relation to a starting point which can be a station or a balise. The advantages with this approach are: a direct comparison between the velocity estimated by accelerometers and the velocity measured by tachometer is possible and the estimation of the travelled distance can be reset in correspondence of a balise.

Considered the good results of this algorithm, the contribution of magnetometer and GPS is not taken into account. Moreover with the one dimensional motion strategy a good estimation for yaw angle isn't so important as the 3D motion and the effort of magnetometer is little; at the same time calculating travelled distance of the train by GPS can introduce a large error.

Figure 2 shows a block diagram for INS/ODO algorithm. The green blocks are input from sensors. A Kalman Filter for gyroscopic measurements is implemented to estimate Euler angles and their derivatives. Orientation Reset is a functionality to reset orientation estimation that is then used to compensate gravity from accelerometer sensors. Because train motion is considered as one-dimensional motion the equation for Gravity Compensation is not (3) but

\[ f^b = f^b + R^b_n g \]

which becomes, being \( g = [0 \ 0 \ 9.81] \),

\[ f^b_s = f^b_s - \sin(\theta) g \]

for longitudinal acceleration, where \( \theta \) is the line gradient.

Kalman Filter for accelerometric-body frame measurements is implemented to estimate acceleration and velocity. At the same time wheel angular speed sensor provides the wheel velocity and acceleration profile.

A comparison between acceleration calculated by tachometers and by Accelerometric Kalman Filter establishes the state of the system (accelerometric criterion): good adherence if the difference between accelerations is less than a threshold, slipping or sliding if it's higher. In the first case the output velocity is directly the tachometer one, otherwise the velocity estimation from Accelerometric Kalman Filter.

Then it's possible to integrate velocity estimation to find the estimate of the travelled distance, which can be reinitialized when the train passes on a balise.
VI - Testing

The innovative cooperative odometric algorithm described in Chapter V was tested using a wide set of simulated data. In particular, a complete three-dimensional multibody model of a railway vehicle, developed by Dept. of Energy Engineering, University of Florence using Matlab-Simulink™ [31, 32], can simulate various working conditions, with arbitrary tracks, including ones which may stress the sensor behaviour (low adhesion between the wheels and the rails for GIT, and curves or line gradient for inertial sensors).

Simulated data to test INS/ODO odometric algorithm and to highlight all critical aspects of the sensors, may have the following characteristics:
- long time running: this feature causes integration error of INS to be high.
- degraded adhesion: tachometers can't provide true value of velocity.
- line gradient: an estimation error for this parameter becomes ten times higher as accelerometer error (see equation 6).
- curves: a good estimation of the line gradient in the Gyroscopic Kalman Filter is influence by a good estimation of yaw and roll angles which appear with a curved path.

In this work we show six test-paths that include all the aspects just described.

Path n°1: straight and level railway line, about twenty kilometers long, with conditions of low adhesion and phases of traction, coasting and braking.
Path n°2: straight railway line, about 20 kilometers long, track gradient of 1% (uphill and downhill) with conditions of low adhesion and phases of traction, coasting and braking.
Path n°3: straight railway line, about 20 kilometers long, track gradient of 2% (uphill and downhill) with conditions of low adhesion and phases of traction, coasting and braking.
Path n°4: straight railway line, about 20 kilometers long, track gradient of 3% (uphill and downhill) with conditions of low adhesion and phases of traction, coasting and braking.
Path n°5: straight railway line, about 20 kilometers long, variable track gradient from 1% to 3% (uphill and downhill) with conditions of low adhesion and phases of traction, coasting and braking.
Path n°6: railway line with straight and curved portions, about 20 kilometers long, track gradient of 3% (uphill and downhill) with conditions of low adhesion and phases of traction, coasting and braking.

Because INS/ODO algorithm has a stochastic behavior due to noise of IMU, its performance can't be evaluated with a single run, but after a lot of runs that differ each other from input noise of sensors.
Then there is the need to join the results for each path and calculated a performance parameter to test the accuracy of the algorithm.

As performance parameter, for each path, we have calculated the percentage of time the error between true velocity and velocity estimated with INS/ODO algorithm meets ERTMS requirements described in [23,24,25,26]. The average respect to the number of runs can be compared with the performance parameter calculated for SCMT algorithm.

**VII - Results**

We report the results of the INS/ODO algorithm, showing:

- a plot of the velocity profile for INS/ODO algorithm compared to the true velocity, the velocity profile estimated with classical SCMT algorithm and the velocity measured by the tachometer in the case of Path n°6.

![Figure 3: Velocity profile Path n°6](image)

- a plot of the error velocity profile for INS/ODO algorithm compared to error velocity for classical SCMT algorithm and ERTMS requirements in the specific case of Path n°6.

![Figure 4: Error velocity profile Path n°6](image)
a table with the comparison between the percentage of time the error between true velocity and velocity estimated with SCMT algorithm doesn't meet ERTMS requirements and the average respect to ten runs of the percentage of time the error between true velocity and velocity estimated with INS/ODO algorithm meets ERTMS requirements for each run.

<table>
<thead>
<tr>
<th>Path</th>
<th>SCMT (%)</th>
<th>INS/ODO (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>n°1</td>
<td>20.8587</td>
<td>2.8082</td>
</tr>
<tr>
<td>n°2</td>
<td>20.1563</td>
<td>2.5431</td>
</tr>
<tr>
<td>n°3</td>
<td>19.9791</td>
<td>2.3329</td>
</tr>
<tr>
<td>n°4</td>
<td>21.3677</td>
<td>0.9840</td>
</tr>
<tr>
<td>n°5</td>
<td>20.4779</td>
<td>1.2018</td>
</tr>
<tr>
<td>n°6</td>
<td>21.7160</td>
<td>2.6014</td>
</tr>
</tbody>
</table>

Table 1: Comparison between performance parameter

Velocity estimated by INS/ODO meets always ERTMS requirements except in the final brake when the axle is locked for a time longer than the average time of wheel locking. Performance parameter is best for Path n°5, because Gyroscopic Kalman Filter tuning is optimized for a track gradient of 3%, but we can see that guarantee very good results also for the other paths.

High accuracy in the velocity estimation turns into a high accuracy for position estimation as shown in Figure 5, where error position between true position and position estimated by SCMT and INS/ODO algorithm are plotted, assuming a balise reset each 3 kilometers.

![Figure 5: Error position profile Path n°6](image)

**VIII - Conclusions**

This paper presents a innovative cooperative odometric algorithm which fuse the information from the different sensors: one tachometer and a IMU. The main features of the algorithm have been described and the conditions in which sensor output signals have a low reliability have been simulated through a complete three-dimensional multibody model of a railway vehicle.

A series of train runs obtain by simulations with a wide range of working and track configurations have been used as tests.

The preliminary results show a significant improvement of position and speed estimation respect to classical SCMT algorithm using as performance parameter the percentage of time the error between true velocity and velocity estimated with INS/ODO algorithm meets ERTMS requirements.

Further activities will be carried out in order to test algorithm performances using a wide set of experimental train runs, using a HIL (Hardware In the Loop) board.
References


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

[27] EEIG ERTMS Users Group, “Performance Requirements for STMs”, Reference EEIG Subset-041, Issue 2.0.0, 30/03/00.


[29] El-Sheimy, N. Inertial techniques and INS/DGPS Integration, ENGO 623- Course Notes, Department of Geomatics Engineering, University of Calgary, Canada (2004)


