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***Abstract*— Positioning accurately and safely a train is nowadays a great challenge. That includes currently available railway sensors and new candidate sensors for data fusion. Global Navigation Satellite System and Inertial Measurement Unit sensors arise as prominent technologies to incorporate in railways. Although satellite-based train localization tests can be found in the scientific literature, there are no common criteria to evaluate the performance of the positioning achieved. In this paper, a series of criteria is defined and justified in order to be able to evaluate the most recent and relevant works related to train positioning. The results of this comparative analysis are gathered in tables, where the criteria defined are applied to the works compiled. According to the results obtained, a research gap in safety related applications is found. It is concluded that the economic viability of given solutions should be explored, so as to design an on-board train-integrated positioning system.**

***Index Terms*— Inertial sensors, satellite positioning, train navigation, data fusion, ground truth.**

I. Introduction

ALTHOUGH it may seem strange, nowadays, no train is positioned safely in an absolute reference frame. This means that railway operators cannot know the position of a train in precise longitude and latitude coordinates. This does not mean the railway management system is unsafe, because there are other techniques used [1]. The most usual system is one based on a beacon. The railway track is divided into so-called cantons. At the beginning of each canton, a beacon (or balise in railway jargon) is placed. When a train passes over it, the traffic management system detects that a train is in that canton (usually the length of the train is measured with axle counters). If another train is located right after this canton, the driver is notified and if there is no response after a while, the train is stopped automatically by its Automatic Train Protection (ATP) system. It is within this signaling system that odometry plays a key role in determining where the train is.

Odometry can be defined as the use of data from motion sensors in order to estimate changes in position over time. In recent years, the number of sensors available for odometry has increased significantly. These new available positioning sensors have found a gap in railway applications, and they can supplement the limitations of conventional sensors, as shown in Table I [2]–[5].

With the new paradigm of sensors available for positioning, their classification is required. Most authors have divided them into on-board sensors (tachometers, inertial sensors, satellite-based positioning systems, etc.) and infrastructure equipment (balises, track circuits, etc.) [1], [6]–[8]. In some cases, a more refined classification is made, based on the fundamentals of the sensor's technology [5]. A general sensor classification is shown in Table I, taking into account other authors works [5], [9].

Typical railway sensors include Doppler radar, the wheel sensor (also called a tachometer [2], [10], [11] or odometer [3], [5], [12], and the Balise transponder. Global Navigation Satellite System (GNSS) and Inertial Measurement Unit (IMU) are the main prominent fields for research. Eddy current sensors are a rather new kind of sensor, which recent research has demonstrated to be applicable as speed sensors [3], [6], [13]. In order to integrate sensors, data fusion is required [7], [13].

The design of train positioning architectures focused on train-integrated positioning systems itself presents many challenges. The first one is to overcome the inherent maintenance cost of infrastructure equipment [6], [14]–[16]. Track equipment is exposed to different weather conditions (temperature changes, ballast blows, rain, snow, etc.) as well as sporadic acts of vandalism, because it is installed in an open sky environment [17], [18]. Consequently, the repair and replacement of these devices contributes to increase their maintenance cost. The second one is also related to track equipment but under the interoperability point of view. Due to the historical deployment of railways, different railway management and signalling systems can be encountered over the world [1], [19]. This heterogeneity makes complicated the interoperability between countries. To overcome this limitation, Europe is deploying the European Rail Traffic Management System (ERTMS) to harmonize railway rules and regulations [19]. Future architectures of any kind of development related to interoperability shall fulfill ERTMS requirements. The third challenge is to validate the designed architecture as safety-critical, based on railway performance requirements [14].

This paper aims at presenting train positioning solutions and evaluating them based on common parameters and criteria (e.g. the sensors and algorithms used, the tests made for validation, the results obtained and analysed, etc.). The main contribution of this paper is the search for research gaps in train positioning and the establishment of future standpoints.

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TABLE I

TRAIN POSITIONING SENSOR CHARACTERISTICS

		Usual sampling frequency	Absolute positioning	Relative positioning (Dead--reckoning)	Position provided	Velocity provided	Long-term solution (large baselines)	Short-term solution (short baselines)	Instantaneous solution	Signal--denied problem	Slip and slide phenomena	Environment impact
On-board equipment	Doppler radar	N/A	No	Yes	No	Yes	No	No	Yes	No	No	Yes
	Eddy current sensor	N/A	No	Yes	No	Yes	No	No	Yes	No	No	No
	Wheel sensor	20Hz	No	Yes	No	Yes	No	No	Yes	No	Yes	Yes
	IMU	100Hz	No	Yes	No	No	No	Yes	Yes	No	No	No
	GNSS	1Hz	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Track equipment	Balise transponder	N/A	No	Yes	No	No	No	Yes	Yes	No	No	Yes

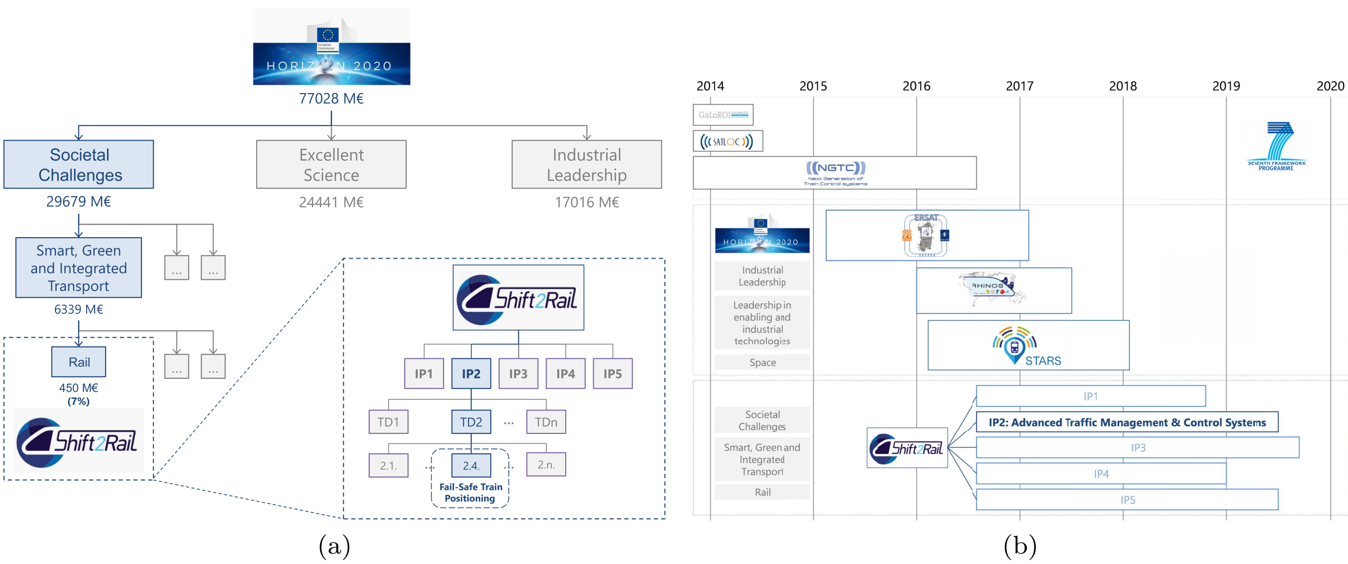

Fig. 1. European projects on train positioning: (a) Horizon 2020 and S2R breakdown. (b) Chronological train positioning context inside S2R and previous projects (GaLoROI, SATLOC, NGTC, ERSAT, RHINOS and STARS) feed.

Once the problem statement is introduced, in Section II the state of the art is presented. In Section III relevant works are evaluated by criteria defined and justified by the authors of the present paper. Finally, this paper's conclusions and future lines of research are described.

II. STATE OF THE ART

Over the last decade, important efforts have been made with regard to satellite-based positioning systems in order to adapt them to civilian applications (e.g. pedestrian and vehicle navigation). The development of Galileo (Europe) and BeiDou (China) are examples. The application of these constellations for train positioning is one of the main objectives of the European Space Agency (ESA) and the European GNSS Agency (GSA). As a sign of its interest, several projects have been funded by these institutions (INTEGRAIL [20], [21], ECORAIL [22], LOCOLOC [23], etc.).

In this section, the last three years of European research projects that have been focused on train positioning are presented. In order to have a general overview of train positioning research, the principal aims and the preceding projects are explained too. Later on, the most relevant works done in this context and the different authors' perspectives are discussed.

A. Train Positioning Research Projects

The railway sector has always been present in different European research programs developed in recent years (e.g. FP7 and Horizon 2020). Accordingly, there is a lot of information published about this topic. So, the following section aims at highlighting the most relevant conclusions, focused mainly on train positioning projects.

Horizon 2020 is the biggest European research and innovation program ever [24]. It is divided into three main areas, as shown in Figure 1a. Within it, all the investigation activities related to the railway are collected in Shift2Rail (S2R) [25].

S2R is the first European rail initiative that seeks research and innovation market-driven solutions to be integrated into innovative rail products [25], [26]. In order to tackle more specific objectives, 5 innovation programs (IP) have been designed, as shown in Figures 1a and 1b, where train navigation is tackled in the IP2 (Advanced Traffic Management and Control Systems). In the present paper, only projects based on Horizon 2020 are described, since it has been concluded that the know-how and conclusions of older research has been included in these.

ERSAT-EAV (ERTMS on Satellite Enabling Application and Validation) is the very first project launched inside S2R, as shown in Figure 1b. The purpose is to verify the suitability of GNSS as the enabler of a cost-efficient and economically sustainable ERTMS signaling solution for railway safety applications [27]. It includes a measurement project, but it goes further, looking for a systematic solution (implemented, tested, and validated for safety applications).

RHINOS (Railway High Integrity Navigation Overlay System) is focused on applying GNSS in the railway context while ensuring architectures of high integrity. Its objective is to increase the use of GNSS to support the safety-critical train localization function for train control in emerging regional and global markets [28].

STARS (Satellite Technology for Advanced Railway Signalling) is meant to fill the gap between the needs of an ERTMS for safety critical applications and GNSS services. The key objectives are the development of a universal approach to predict the achievable GNSS performance in railway environments and the quantification of the economic benefits this technology can bring [29]. In essence, the aim is to include GNSS into ERTMS, maintaining both the safety and the interoperability of the system. The input of this project is the different work done in NGTC and ERSAT projects as well as older ones (GRAIL, LOCOPROL, LOCOLOC, etc.). The outputs should be the analysed data obtained from different railway tests.

A further survey of the research projects about the inclusion of GNSS in railway signaling systems is collected in [19].

B. Train Positioning Applications

As shown in the previous section, the applicability of GNSS to trains is of great interest. Nevertheless, its application is closely related to train safe-odometry, which necessitates the fulfillment of safety-critical requirements. These requirements are based on strong normative and this has made its introduction relatively slow [19].

GNSS presents limitations in signal-denied areas, such as tunnels, urban environments, and foliage. In such areas, no GNSS solution is available. Consequently, the safety integrity of the positioning system is jeopardized. The limitations of the availability of a GNSS signal in those areas is one of the main reasons why extra sensors are needed. Thus, researchers have focused on its integration via multisensory data fusion.

The very first article on data fusion related to train navigation presents candidate sensors for positioning and outlines a generic sensor fusion architecture [7]. The algorithms and sensors presented set the course for any later research, although some of the characteristics and technologies presented are nowadays obsolete (e.g. the selective availability in GPS signal and best accuracy reached, the nonexistence of an IMU technology based on Micro Electro Mechanical Systems (MEMS), a maximum sampling frequency of GNSS limited by 1 Hz).

Since that first publication, and in parallel with the development of technology (e.g. new GNSS constellations, the inclusion of MEMS in consumer electronics, etc.) many research articles have been published. In the following, some of the most important ones are highlighted.

Many authors have focussed on the localization of land vehicles and have extrapolated the architectures designed from this area to the railway context. Most of the literature available up to date are based on this idea [4], [12], [30]. Although trains are also land vehicles, they have special features (railway track constraints, slip and slide phenomena, smooth changes in trajectories and altitude, etc.) that necessitate a special architecture.

One of the first articles published related to this issue was a GPS and IMU fusion architecture [9]. It presents an explicit explanation of the equations needed to model the system as well as the results of field tests. It can be concluded that the same architecture nowadays will give more accurate results since the selective availability of GPS signal is now disabled. The system's overall cost will be lower too, by installing an IMU based on MEMS instead of the original one.

Other authors have tackled the train positioning problem by taking into account the dynamics of the train and the restrictions imposed by the track. The most relevant work in this sense has been done in a collaboration between the University of Florence and the University of Siena [10]. An implementation of a tachometer and a 6-DOF IMU was carried out combined with a train multibody model and the computation of multiple Kalman filters. The solution had a maximum error of about 20 m in travelled distance and 1.5 m/s in calculated speed, so it fulfills the European Train Control System (ETCS) requirements in terms of accuracy according to [31]. This work has some preceding papers, where the state of the art of railway sensors was presented and a Tachometer-IMU architecture discussed, building a railway vehicle dynamic model and developing a system with improved wheel velocity measurements [32]–[34].

A rather original standpoint is presented in [8] and [35]–[37]: instead of 3D positioning, the authors consider a train as a unidimensional vehicle constrained by a track. Thus, the algorithm only needs to solve a 1D problem. Thanks to track map information, the one-dimensional solution is then linked to a 3D map and the train can be located in absolute coordinates.

III. Review of Solutions

In this section, the most recent and relevant research done in the context of train positioning is collected and evaluated in terms of several criteria developed by the authors of the present paper. In the *Methodology* subsection, the definitions of the criteria are justified. In the *Results* subsection, the literature is evaluated based on these criteria.

A. Methodology

The evaluation methodology is divided into 4 steps, which are defined in chronological order. Firstly, the test track is analysed, that is, the environment where the presented papers are focused. Secondly, the used sensors are evaluated. As GNSS and IMU are the new sensors to be integrated into railway environments, their analysis is deeper than that of the sensors conventionally installed in trains. Thirdly, the data measured by the sensors should be treated, so the algorithms

TABLE II
TEST TRACK ANALYSIS

Authors	Test environment	Challenging features test/simulation				Train characteristics		Positioning mode	Test duration [h]	Ground Truth technique
		Slip/Slide	Tunnel	Forest	Urban	Operation mode	Maximum speed [km/h]			
[2]	Sim	Yes	Yes	No	No	VHS	400	3D	0.42	Simulated data
[4]	Exp	No	No	No	No	N/A	N/A	2D	N/A	DGPS solution
[6]	Exp	No	No	No	No	VLS	30	2D	3.00	RailML Database
[10]	Sim	Yes	No	No	No	HS	200	1D	0.16	Simulated Data
[11]	Exp	No	No	No	No	VLS	30	3D	N/A	N/A
[12]	Exp	No	Yes	No	No	HS	250	2D	N/A	N/A
[15]	Exp	No	No	Yes	No	N/A	N/A	2D	1.00	N/A
[16]	Sim	No	No	No	No	HS	200	2D	0.16	Simulated data
[30]	Exp	No	No	No	Yes	LS	70	1D	1.50	IMU + Tachometer
[36]	Exp	No	No	No	No	N/A	N/A	1D	0.03	Topography data
[37]	Exp	No	No	No	No	CS	120	1D	4.00	OSM Database

Acronyms: Experimental data (Exp) and Simulated data (Sim). Very High Speed (VHS), High Speed (HS), Conventional Speed (CS), Low Speed (LS) and Very Low Speed (VLS).

employed for that aim are evaluated. Fourthly, the outputs of the algorithms are analysed.

1) Test Track Analysis: For the test track analysis, 6 criteria have been defined and evaluated in the literature as seen in Table II. In the following paragraphs, each criterion is presented and justified.

Firstly, the test environment defines how the system is tested. In an experimental test, a set of measurements is carried out, in which a train is running on a track. This is the most realistic way to evaluate a system, but it needs a train and a track available to proceed with each test run. In some cases, this option is unfeasible (either the train is not available or there is no permission to run on the track) and a simulated test is carried out. In such a case, a track is modelled in the most similar way to a real one, taking into account the particular characteristics of a railway (radii of the curves, cants, slopes, etc.). In simulated tests, computational and programming efforts are needed in track and sensor signal construction, but more scenarios can be checked without additional cost.

The second criterion is related to the features of the test environment. The track selected for the test runs should have some restricted zones, where a GNSS signal is not available. Wheel and rail adhesion conditions should be degraded in places, as well. In simulated scenarios, these zones are rather easy to consider, but in experimental tests they depend on the track selected. That is why some tracks are more challenging for train positioning (those with large tunnels, urban canyons, foliage, or mountainous environments).

Another criterion related to the test track is the train operation mode. This can be dependent on the test track and type of train employed. Here, they are classified in terms of the maximum speed travelled in the test run (either experimental or simulated). The higher the speed, the smaller is the number of positioning nodes for a given space segment. Consequently, positioning in the same track will be done with fewer points in lines with higher speeds.

The positioning mode represents the number of variables devoted to locating the train. The unidimensional solution is a classical hypothesis in the railway context (a track constrained problem where two degrees of freedom, the cross track direction and vertical direction, are forced to be zero), where the covered distance from a known origin (relative distance) is calculated. In some papers, the relative distance is associated with a digital map that has the absolute coordinates [36], [37]. The bi-dimensional solution (longitude and latitude) is a particularization of the land vehicle localization problem (tri-dimensional) to the railway context, where the slopes are very smooth (up to 2.3 degrees in high speed lines [35]) and, hence, altitude changes can be considered negligible.

The next criterion is the duration of the test. Its justification is based on the huge amount of data that is created with larger test durations, and the associated problems that arise for the data treatment. Especially in research where track databases are used, the evaluation of the test duration is an important issue [37].

Finally, the Ground Truth (GT) technique is evaluated. GT is the reference position used to compare with the solution reached with data fusion algorithm. There exist multiple techniques for generating the GT. The easiest way is access to the railway track operator's data base. Nevertheless, this option is not always possible. An alternative is to use general purpose maps, such as Open Street Maps (OSM) or Google Maps. In these cases, the accuracy of the information provided should be evaluated [37]. Another possible method is the use of carrier phase measurements with reference station corrections in real time (RTK). This solution is proposed in the ERSAT and STARS projects [38]–[40]. However, this technique has limitations as well (GNSS signal availability, fixed base station communication, etc.) [41].

2) Analysis of the Sensors: The analysis of the characteristics of the sensors shown in Table III is focused on GNSS and IMU, which are the candidate sensors for integration into the railway environment. There are two main reasons why they were chosen for a detailed analysis. First, the know-how about these sensors and their application to the railway sector is quite limited, as is reflected in the amount of research effort that has been carried out in these areas [25], [27]–[29] [27]. Second, the market solutions available for GNSS receivers and IMU sensors are good in terms of functionality, accuracy and price. This requires an exhaustive investigation of the performance parameters required for railways.

In the case of GNSS, the first evaluation criterion is the receiver type. The GNSS receivers are classified as

TABLE III
SENSOR CHARACTERISTICS

Authors	Candidate sensors characteristics										Currently in use train sensors
	GNSS				IMU						
	Type	Model	Frequency	Cost	Type	Tech	Model	DOF	Frequency	Cost	
[2]	High-end	N/A	1Hz	N/A	N/A	N/A	N/A	6	100Hz	N/A	Tachometer (20Hz) Balises Reader (300m)
[4]	High-end	N/A	1Hz	N/A	N/A	N/A	N/A	9	1Hz	N/A	Balises Reader (500m)
[6]	High-end	Septentrio Aste-Rx3	N/A	7100€	-	-	-	-	-	-	-
[10]	-	-	-	-	Customer Grade	MEMS	ECM S.p.A	6	N/A	N/A	Tachometer (N/A) Balises Reader (1000m)
[11]	High-end	Trimble Ashtech GG24	10Hz	1000€	Tactical Grade	MEMS	Watson BA604	6	125Hz	N/A	Tachometer (20Hz)
[12]	High-end	iNAT RQT4003	N/A	N/A	Navigation Grade	RLG	iNAT RQT4003	6	N/A	N/A	Tachometer (N/A)
[15]	N/A	N/A	2Hz	N/A	-	-	-	-	-	-	Doppler Radar (N/A) Balises Reader (N/A)
[16]	High-end	Trimble Ashtech MB100	N/A	900€	-	-	-	-	-	-	Tachometer (N/A)
[30]	-	-	-	-	Customer Grade	MEMS	MEGGITT SX43030	6	N/A	2800€	-
[36]	High-end	Septentrio Polar-Rx3	1Hz	N/A	Navigation Grade	MEMS	xSens MTi	6	10Hz	1500€	-
[37]	Low-end	u-blox LEA6T	1Hz	31.5€	Navigation Grade	MEMS	xSens MTx	6	200Hz	N/A	-

high-end or low-end, depending on their functionalities (multi-constellation, multi-frequency, augmentation systems, corrections by code/carrier phase analysis, etc.) and, consequently, the performance requirements reached and price [14]. The sampling frequency in use has the utmost importance in order to evaluate the number of samples measured in a given space. The limitation of the selected sampling frequency is given by the receiver itself, that has a maximum allowable value. The manufacturer and model are used to identify the receiver.

In the case of IMU, the criteria presented are similar to those for GNSS. The IMU type, however, is classified into customer grade, navigation grade, or tactical grade, depending mainly on the bias stability [42]. However, other parameters, such as non-linearity, scale factor, or misalignment seem to be different too [43]. Furthermore, the technology employed inside the accelerometers and gyroscopes is presented. Depending on the performance wanted, different technologies are used: for tactical and navigation grades, the Ring Laser Gyroscopes (RLG) and Fiber Optic Gyroscopes (FOG) are predominant, whereas for consumer grade, MEMS seems to be the best trade-off between performance, size, and cost [42]. It is concluded that MEMS technology is the only one that is economically affordable for on-board equipment [44]. However, in future work, railway electromagnetic compatibility norms should be analysed for the case of MEMS sensors. In the very same way as GNSS receivers, the IMU manufacturer and model are used to identify the sensor. The very same criteria are used in sampling frequency and price.

A different criterion, added for the IMU, is the number of degrees of freedom (DOF). The DOF of an IMU represents the number of independent measurements that it is able to take. In a typical configuration, the IMU is formed by a tri-axial accelerometer and a tri-axial gyroscope, thus it has 6 DOF. However, in some recent land vehicle applications, a tri-axial magnetometer is added (9 DOF) so as to correct yaw drifts and attitude errors [45], [46]. In addition, a barometer can be installed (10 DOF) in some other applications in order to overcome the lack of precision of GNSS in the altitude coordinate [47].

The last sensors presented in this analysis are those currently available and installed on trains. As they are the usual sensors in the railway environment, a few criteria are used to evaluate them according to the data fusion algorithm. For instance, the frequency of the measurements: in Doppler radars and tachometers, the sampling rate is noted, whereas in balises the spacing between them is selected because their measurments depend on the train speed, location, or safety requirements.

3) Analysis of the Data Fusion Algorithm: Once the measurement system is defined by the sensors used in the test environment, a data fusion is executed. Multi-sensor data fusion relies on Bayesian theory and, more specifically, on a recursive Bayesian estimation that is used to solve the hidden Markov model (HMM) [48]. At this point, mathematical aspects and practical issues are related to each other to evaluate the data fusion techniques employed, as shown in Table IV.

The first criterion is the framework or the programming environment used to execute the data fusion algorithm. Then, the the algorithm implemented is analysed. Under recursive Bayesian estimation, the algorithms are classified into optimal filtering and non-optimal filtering [48]. Based on the literature in the railway context up to the present, the main representative algorithms of each group are the Kalman Filter (KF) and Particle Filter (PF), respectively.

The KF is a recursive linear estimator which successively calculates an estimate for a continuous valued state, which evolves over time, on the basis of periodic observations of the state [49]. Based on this definition, the general procedure behind the algorithm can be seen: the KF predicts a new state by knowing the previous state and a dynamic model of train movement. Then, it uses sensor measurements to correct the prediction made. The reason why it is classified as an optimal filter is due to its way of weighting the measured value and the

TABLE IV
DATA FUSION ALGORITHM

Authors	Framework	Algorithm	Implementation	Number of state variables	IMU to INS transformation	GNSS parameters	GNSS/IMU integration
[2]	Matlab	TS-FKF	Indirect	15	N/A	PVT solution	LC
[4]	Matlab	EKF	Indirect	13	Quaternion-based	PVT solution	LC
[6]	C++	IEKF	N/A	N/A	-	PVT solution	-
[10]	Matlab/Simulink	KF	Direct	6	Quaternion-based	-	-
[11]	Simulink	IF	Indirect	9	DCM based	PVT solution	LC
[12]	N/A	EKF	Indirect	25	N/A	Pseudorange	TC
[15]	N/A	N/A	N/A	N/A	-	PVT solution	-
[16]	Matlab	PF	N/A	6	-	PVT solution	-
[30]	Matlab	EKF	Direct	11	N/A	-	-
[36]	Matlab	PF	N/A	8	N/A	Pseudorange Doppler observable	TC
[37]	JAVA	RBPF	N/A	12	N/A	PVT solution	LC

Acronyms: Two-Staged Federated Kalman Filter (TS-FKF), Extended Kalman Filter (EKF), Iterated Extended Kalman Filter (IEKF), Kalman Filter (KF), Information Filter (IF), Particle Filter (PF), Rao-Blackwellized Particle Filter (RBPF), Loosely Coupled (LC), Tightly Coupled (TC).

predicted value, whcih is designed so that the error variance is a minimum [50].

However, the KF has some limitations in that it assumes the dynamic and measurement models are linear and normally distributed (Gaussian). In the railway context, the dynamic model of the train can be highly non-linear due to suspension stages, the wheel–rail adhesion law, etc. [51]. To overcome the restriction to linearity, the Extended Kalman Filter (EKF) can be used. In it, a linearization procedure is applied (a Taylor series expansion) to either the dynamic model or the measurement model.

In other cases, the Gaussian assumption is not fulfilled, and then the posterior probability density function should be modeled. With that aim, sub-optimal algorithms are used [48]. Some of them are variants of the KF, such as the Unscented Kalman Filter (UKF) or the Curvature Kalman Filter (CKF); others, such as the PF, present a new procedure that differs from the assumptions of the KF.

Depending on the algorithm employed, an implementation criterion is defined. The algorithms developed under the KF context can be implemented either directly or indirectly [52]. The direct implementation assumes that the measured states and the space states are equal, whereas in the indirect implementation, an error space state is defined. One of the advantages of the indirect implementation is that the errors of the states can be modelled and compesated in each iteration.

The number of navigation problem states should be at least equal to the number of unknowns in the position and velocity. In 3D positioning, the minimum number of states will be 6 (tri-dimensional position and tri-dimensional velocity). In the indirect implementation of the KF, the more state variables are used, the more error propagation parameters are modeled. But this implies using larger dimensional matrices, and consequently a higher computational burden.

The final three criteria are related to the IMU and GNSS data treatment techniques. First, a transformation is made between IMU sensor measurements (accelerations and turn rates) and the IMU sensor solution (position and velocity). This process is called mechanization, and a transformation from the body frame to the navigation frame is made. The resulting solution is called the Inertial Navigation System (INS) solution. The method of Euler angles, the direction cosine matrix (DCM), and a quaternion-based method are the most popular techniques for this process [53]. A comparison of these three methods is presented in [54].

Second, the GNSS receiver measured parameters are shown. In general, a GNSS receiver can give raw measurements of the received signal from satellites (Pseudorange, Code phase, Doppler shift) or a treated solution called the PVT (Position, Velocity and Time).

Third, the IMU and GNSS solution integration techniques are described. On the one hand, in a loosely coupled integration scheme, the filter updates the PVT solution of the GNSS receiver and the INS solution [36]. On the other hand, in a tightly coupled integration, the GNSS and IMU raw measurements are taken and fused. One of the advantages of a tightly coupled integration scheme is that the IMU accelerometers and gyroscopes can be recalibrated in real time [53]. On the contrary, some low-end GNSS receivers cannot provide raw measurements: therefore, tightly coupling is not feasible for those receivers.

4) Analysis of the Research Results: Finally, the criteria for the evaluation of the results are presented in Table V. These criteria are explained in the following paragraphs. The first criterion for the evaluation of the results is when were the results computed. The typical research analysis establishes that the data treatment is accomplished once the measurements are finished (post-processed or off-line). However, a real time data record and analysis (on-line) is of the utmost interest for train positioning because it represents a more realistic way to validate an on-board positioning system. This functionality, nevertheless, depends on the calculational power of the hardware.

Another relevant criterion is the application for which the research was intended. Depending on whether it is a safety or a non-safety application, the requirements associated to the designed system are different. The application will greatly determine the variables to be analysed in the research results.

In the case of non-safety applications, specific requirements can be analysed or a comparison of the results can be carried out in a more general way. In most cases, the research objective is focused on technological availability and technical viability studies. Consequently, there are defined different error metrics in order to evaluate the performance of the solution.

In safety-critical applications, the governing norms are rather severe [19]. In railway applications, the reliability, availability, maintainability, and safety (RAMS) of the proposed system should be analysed according to the norm in EN 50126 [55].

Based on a RAMS analysis, the Safety Integrity Level (SIL) of the system must be determined. SIL prescribes requirements for safety-related functions so as to reduce and attain an acceptable risk [19]. The SIL related specifications are defined by qualitative measures and by a scale of Tolerable Hazard Rates (HTR) [19]. The higher the risk, the higher the SIL level and hence the requirements to be fulfilled. In the railway context, for a train protection system, the positioning is defined as SIL4 due to the dangerous situations that could arise from under- or over-estimating a train's position along the track [56].

B. Results

Using the methodology established and the criteria defined in the previous section, the most relevant literature of the last three years in the field of train positioning have been collected. The research presented here was done with different purposes and although common aspects have been highlighted, some others cannot be evaluated. The classification of the literature has been made in order of the appearance in the writing of the present paper.

The criteria that cannot be evaluated have been separated into two different types. The first refers to Not Available (N/A), which means that this criterion was used in the research but is not available in the publication. The second one is the hyphen (-), which refers to the fact that the criterion was not taken into account.

In Table II, the *Test track analysis* is collected. Most of the papers employ the experimental data obtained from systematic measurements in order to validate the research [4], [6], [11], [12], [14], [30], [36], [37]. Less than one-half of the publications (5 out of 11) use a challenging environment for the positioning sensors in their analysis. 60% of the challenging environments are real scenarios, where the train has pass through a tunnel, a forest, or an urban environment. According to the train operation mode, only 4 of these were run in high speed environments, and 2 of them are simulated environments. In positioning mode, the 2D solution is the most popular (5 out of 11) but a 1D solution accompanied by a track map is also much used (4 out of 11). The test duration seems to be quite erratic, because there is no single pattern in the literature (some are for 4 hours [37] whereas others are limited to 90 seconds [36]). Neither in the case of the GT is there a common information source. Note that some databases are not very accurate (5 meters imbalance between real and downloaded data), as has been demonstrated in [37].

In Table III, the positioning sensor characteristics are summed up. As mentioned previously, the comparison is focused on GNSS and IMU sensors. Beginning with the GNSS receivers, almost all the literature uses high-end type receivers, except for [37]. In the case of models, two papers use AsteRx/PolarRx (one is the preceding model of the other) receiver of the manufacturer Septentrio. One of the reasons why the authors have decided to use this model is related to the use of the same model in the ERSAT-EAV and STARS European research projects [38]–[40]. The sampling frequency, when it is provided, can be considered quite uniform, at 1 Hz (4 out of the 6 available) and coherent with the technology itself. The cost of the high-end type receivers in comparison with low-end type is very significant (two orders of magnitude approximately). This demonstrates that apart from their extra functionalities (multi-constellation, multi-frequency, differential GNSS, RTK, etc.) the internal signal analysis and PVT calculation algorithms, the error correction models, signal adaptation filters, etc. significantly increase the cost of the receiver.

In IMU sensors, there is a consensus on the use of MEMS technology, as was predicted in the previous section. There is only one exception, [12], where an RLG type INS is used. Although the MEMS technology is predominant, it uses different grades of sensor. Customer grade, navigation grade, and even tactical grade MEMS technology IMU sensors are presented in the analysed literature. A model made by the manufacturer XSens is used in the research reported in two different papers. The models presented (MTi and MTx) are widely used in land vehicle positioning [57], pedestrian localization [58], [59], and robotics [60]. Most of the research is based on 6-DOF measurements (7 out of 8) despite the availability of magnetometer data in some of them [11], [36], [37], but not used. The sampling frequency is not uniform at all, although mostly (3 out of 5) 100 Hz or higher is used [2], [11], [37].

As to the railway sensors, the tachometer is the most used sensor (5 out of 7) and its sampling rate is 20 Hz. In the case of balises, the spacing distance depends on the maximum allowable speed of the train. Thus, in a very high speed line, the spacing is lower (400 km/h and 300 m spacing) than in a high speed line (200 km/h and 1000 m spacing).

In Table IV the characteristics of the data fusion algorithm are highlighted. The predominant framework or programming environment is Matlab (6 out of 9). This is justified because of the nature of Bayesian estimation, which relies on multiple matrix operations, and this environment is appropriate for that [61]. As to the type of algorithm, all of them are based on recursive Bayesian estimation although the procedure employed for the data fusion can be quite different: most of them are variations of KF (7 out of 10) but some are related to PF (3 out of 10). The indirect implementation is more popular (4 out of 6) than the direct one because of the advantages presented before. The number of state variables is not uniform. All of them take position and velocity as state variables, but from this point on, the number of states associated to the errors modelled (indirect implementation) can be very different. There is not too much information presented about the transformation of the IMU measurements to the INS solution (3 available data out of 8 papers using IMU). In GNSS parameters, most of the papers employ the PVT solution (7 out of 9), which makes the loosely coupled integration scheme a common architecture.

TABLE V
RESEARCH RESULTS ANALYSIS

Authors	Analysis mode	Application		Position and speed variables analyzed (Error metrics)	Values
		Type	Requirements		
[2]	Off-line	Non-Safety	No	Mean RMS Error	1.04m
[4]	Off-line	Non-Safety	No	Maximum RMS Error	1.5m
[6]	Off-line	Non-Safety	No	Track selectivity	94.2%
[10]	Off-line	Non-Safety	ETCS	Instantaneous Error in covered distance Instantaneous Error in speed	N/A
[11]	Off-line	Non-Safety	No	N/A	N/A
[12]	On-line	Non-Safety	No	Maximum Total Cumulative Error	27.29m
[15]	Off-line	Safety	EN50126 (RAMS and SIL)	-	-
[16]	Off-line	Non-Safety	No	Mean RMS Error Variance RMS Error	0.135m 0.136m
[30]	Off-line	Non-Safety	No	Cumulative Error in covered distance	6.4km
[36]	Off-line	Non-Safety	No	Mean RMS Error Maximum RMS Error	0.73m 1.46m
[37]	Off-line	Non-Safety	No	Track selectivity	99.7%

In Table V, the research results are analysed. Beginning with the analysis mode, it is clear that the usual analysis of the results is based on post-processed data (10 out of 11). The reasons for this can be explained by many causes: approvals from the infrastructure managers to set up equipment, computational power requirements not fulfilled by on-board equipment (since on board units are dedicated devices to protect the train but not to record such large data sources), etc. As to the application, although most of the publications do not compare their results to specific requirements, in [10] the European Train Control System (ETCS) requirements [31] are analysed in order to evaluate the architecture proposed. In another paper, local governmental requirements are presented [5]. However, almost all the literature focusses on non-safety related applications (10 out of 11). Consequently, the implementation of such research in real train scenarios has a long way to go as long as safety requirements are not analysed. The only paper, [14], that analysed the railway safety-related performance properties (RAMS) calculates the following variables. The reliability is evaluated by the mean time to failure (MTTF), with a value of approximately 185 s. In addition, the solution availability reaches 82.26%. From the safety point of view, the hazard rate (HR) is divided into forest ($HR = 5.25 \times 10^{-2} h^{-1}$) and open area ($HR = 5.25 \times 10^{-7} h^{-1}$). The solution overall achieves SIL2.

In the papers presented, each author decides on the variables to be analysed. So, it is quite complicated to evaluate these results with the same criteria. However, some similar variables are collected and commented on the in the following. The maximum root mean square (RMS) error is approximately 1.5 meters, whereas the mean RMS error has a wider range (between 0.135 and 1.04 meters). Another parameter in common use in two papers is the track selectivity (i.e. the percentage of cases in which the track selection is carried out correctly) which is higher than 94% in two cases (94.2% and 99.7%).

IV. DISCUSSION AND CONCLUSIONS

In the present paper, a survey of the most recent and relevant train positioning solutions was presented and evaluation criteria were set in order to detect research gaps for future implementations. Based on this, several conclusions will be presented in this section. Analysing the tested track characteristics, more complex simulated environments can be developed. They should cover the majority of the situations in which the odometry can fail (e.g. poor wheel–rail adhesion, GNSS signal denied areas such as urban canyons, foliage, tunnels, and bridges, changes in meteorological conditions, system power supply turn-off, sensor failures, etc.). However, these simulated environments should also be tested in real scenarios (validation). Both simulated and real environments should be very high or high speed lines because this type of track seems to be the most critical (the measurements of the IMU and GNSS are taken in the largest space section).

A GT establishment technique should also be investigated and the quality of the method evaluated. According to the algorithms used to fuse the sensor measurements, the choice criteria should be related to the ability of the algorithm to run on-line. The designed architecture should consider the computational burden of the data fusion system in order to operate in real time. The technical viability of GNSS and IMU integrated solutions for non-safety related applications has been demonstrated by the the literature surveyed here. However, research focussed on safety-critical applications is very limited, and the fulfillment of the safety requirements is not guaranteed for ATP systems.

It seems clear from the current state of research that the eventual train positioning solution will integrate a low-end GNSS receiver and customer grade IMU sensor-based solutions. The economic viability of high-end solutions is unfeasible, due to their hllarge cost (thousands of euros). In this eventual solution, the sensors currently installed on trains (tachometers, Doppler radar, and balise readers) should be included as aided navigation sensors. The research challenge will come in the construction of low-cost (hundreds of euros) architectures that can fulfill the safety requirements.

The selection and justification of the optimum data fusion algorithm as well as the standardization problem of the validation parameters intend to be the most relevant future directions. In future works sensors data (10 DOF IMU and GNSS seems to be most novel sensors in train context) obtained from a test run should be analysed under SIL requirements in order to evaluate Bayesian framework algorithms.

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