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SELECTED APPLICATIONS OF SATELLITE TECHNOLOGIES IN RAIL TRANSPORT

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Abstract:

Global Navigation Satellite Systems (GNSS) are increasingly being used in various modes of transport, including rail transport. When this technology is applied to railway traffic control, it is essential to ensure a high level of safety and reliability. The approval of a railway traffic control system requires a safety analysis, which includes hazard analysis and risk analysis. This also includes GNSS-based solutions in terms of their compliance with safety integrity requirements, i.e. THR (Tolerable Hazard Rate) and SIL (Safety Integrity Level) parameters, as defined in normative documents. In the case of railway traffic control systems, the level of dependability of the determined train position, referred to as position integrity, is very important in ensuring safety. Position integrity is affected by many factors, including: errors due to SIS (Signal-In-Space) propagation, multipath errors, signal interference or GNSS receiver errors. In order to improve position integrity, among other things, new data processing methods can be used to improve the accuracy and reliability of measurements. The paper presents the concept of satellite signal processing for precise determination of the position of objects in selected railway systems. The Kalman filter based model of satellite signal filtration and its selected applications, which were tested in the real condition, was presented. The application of Kalman filtration indicated in the paper is a universal method that improves the estimated measurement parameters and can be used in many applications of satellite systems for railway tasks. The applicability of satellite systems to automatic train operation, defect positioning in automatic and manual flaw detection tests, determining track spatial orientation and train integrity control have been considered. The conducted tests confirmed the correctness of the adopted concept and the model of satellite signals filtration developed for this purpose. According to the authors, the described methods can also be used in many other tasks related to rail transport.

Keywords: *GNSS, Kalman filter, railway transport, automatic train operation, determining track spatial orientation, determination of defects location in rails, train integrity control*

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1. Introduction

Systems using navigation elements for precise air and ground movement control are developed worldwide. One of such systems is the NAVSTAR/GPS (Global Positioning System) developed in the USA. Navigation data acquired from this system is used on a large scale in military technology, maritime and air navigation, as well as in automotive applications. In railway applications, this system is implemented by the railway operators to determine the position of the receiver's antenna located on the locomotive and thus to determine specific coordinates of the whole train or its elements (Marais et al., 2018; Lu et al., 2019). This application is due to the fact that modern safety-related railway traffic control and signaling systems require a large number of diverse track-side infrastructure exposed to devastation (Kornaszewski et al., 2017; Nowakowski et al., 2017). The rapid development of telecommunications and satellite navigation technology creates new opportunities for railways to use digital maps for train control and operation, as well as for positioning and identification of infrastructure elements. Using Kalman filtration as a universal method of improving measurement results can become an important tool in the designing railway systems that use GNSS (Global Navigation Satellite Systems) in their work.

2. Literature review

Autonomous train positioning using GNSS is an interesting alternative to classical positioning solutions based on trackside equipment. This is mainly due to the high cost of installation and maintenance of trackside equipment currently used by infrastructure managers (Losada-Martin et al., 2015; Kornaszewski et al., 2017). Therefore, GNSS technology (in combination with other sensors) may become an alternative solution in the near future. The development of GNSS systems, including GPS and Galileo, means that autonomous train positioning using this technology is the subject of interest and research in many countries (Marais et al., 2017). These GNSS integration activities in the railway sector are being studied, particularly in Europe with programs like STARS (Stamm et al., 2017), NGTC (Gurník, 2016), ERSAT EAV (Rispoli, 2017), ERSAT GGC (Marais et al., 2018) or Shift2Rail IP2 TD2.4 (Fail-Safe Train Positioning) (Flammini et al., 2022) and TD2.5 (On-board Train Integrity) (Sassi et al., 2022). The basis for achieving accurate and reliable train positioning is to reduce position calibration errors (Jon et al., 2017; Liu et al. 2020; Lu et al., 2015). GNSS technology is used in various rail transport applications at different stages of system management and operation, e.g. (Marais et al., 2017; Mrohs et al., 2021; Neri, 2020):

– Train navigation - GNSS can be applied to track train positions in real time.
– Route planning and scheduling - GNSS data can be base to analyse train movements and optimize route plans and schedules.
– Safety and traffic management – data acquired from GNSS can enhance safety on railway tracks by monitoring train speeds, as well as improve traffic management and collisions prevention.
– Passenger information - GNSS data allow to track train location, provide passengers with real-time information, predict arrival and departure times, and any potential delays.

GNSS can provide information about the train's position, however, this can be subject to some errors, such as multipath, signal weakening in tunnels, or atmospheric interference. One of the methods that can allow to obtain a precise estimate of the train's position even in difficult conditions is the use of Kalman filter (Elmezayen et al., 2021; Faruqi et al., 2018; Greiff et al., 2021; Sever et al. 2022). In the context of railway systems, the Kalman filter can be used to improve positioning accuracy by integrating data from different sources and reducing measurement errors and noise (Jia et al., 2022; Spinsante et al., 2020; Wang et al., 2018; Wu et al, 2023; Yuan et al. 2024). Among the activities that improve the safety level of systems using GNSS technologies, mitigation and prevention of threats, as well as counteracting the causes of threats in the various components of these systems are commonly listed (Beugin et al., 2018; Lu et al., 2020; Cai et al. 2020; Aleš 2020, Ji et al., 2021). Eventually, this should provide the appropriate level of safety integrity required for such systems (Shuai et al., 2020; Presti et al., 2018).

3. The application of the Kalman to improve the accuracy of positioning objects and rail vehicles on the track

The appropriate use of the Kalman filter for the estimation of measurement results allows to improve the accuracy of positioning objects and vehicles on the track. The Kalman filter is used for dynamic systems discrete in the time domain. The state of the system is represented by a state vector, which is determined at each step by a linear operator, taking into account the noise associated with imprecise object observations and modelling errors.

The model of the system based on the Kalman filter was presented in Fig. 1.

The system is based on the analysis of the process model and measurement system (Kornaszewski et al., 2017). Process modelling consists in determining the state vector x_k (1) at moment k on the basis of the state vector x_{k-1} at the moment $k-1$ (Chrzan et al., 2019; Kaniewski, 2020):

$$x_k = \Phi x_{k-1} + B u_{k-1} + w_{k-1} \tag{1}$$

Modelling the measurement at k is based on the determination of z_k – observation of the real state vector x_k (2) (Chrzan et al., 2019):

$$z_k = H x_k + \eta_k \tag{2}$$

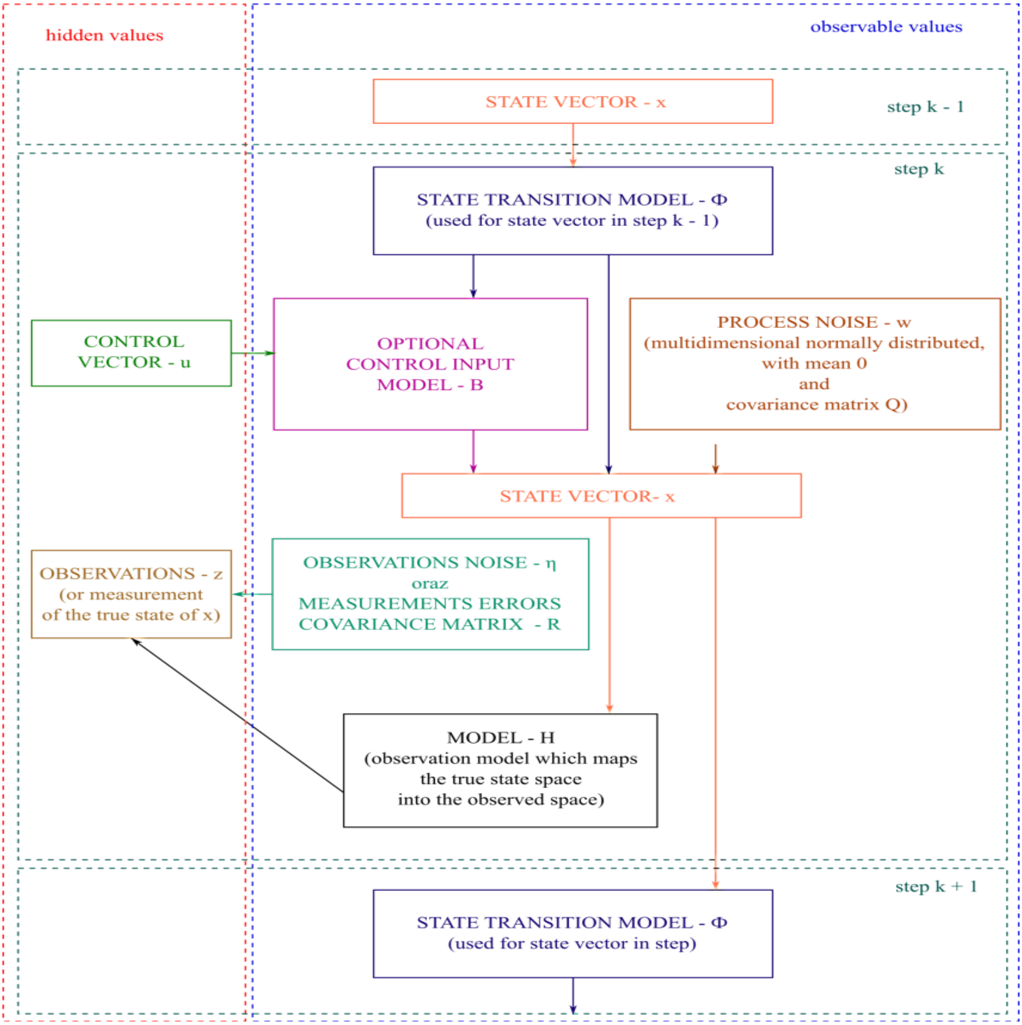


Fig. 1. Model of the system based on Kalman filter (Chrzan et al., 2019)

Kalman filter is a recursive filter. The advantage of this type of filtration is that the estimation of the state at a given time requires only the knowledge of the previous state and the observation vector. Kalman's filtration is divided into two stages of prediction and correction, which interact with each other.
In the first stage - prediction (based on the state vector from the previous step), a priori values are determined, i.e. the estimated value of the state vector and its covariations. In the second stage - correction - the observation data are updated to improve the determined state vector. At this stage, a posteriori values are determined, i.e. the value of the state vector and its covariations. The presented model of the system leads to the design of the Kalman's filter algorithm to the determine of the train position.
The Kalman filter is based on the analysis of data (containing statistical noise) from all measuring sensors, no matter how accurate they are. On the basis of the acquired information, the best estimate of the state vector is calculated. In the described filter, a recursive algorithm is used, so that it does not store all past data and it does not recalculate them in every step. Data processing is carried out sequentially, using the values calculated in the previous step. On the basis of measurements (obtained from different sensors), it is possible to determine inaccessible values (values which cannot be measured) (Truong Ngoc et al. 2019; Boffi et al. 2016; Kaniewski, 2020).
In the analysed model, the direct method of filtration consists in entering data from on-board systems and GPS as measured values into the Kalman filter according to the diagram shown in Fig. 2. The task of the Kalman filter is to estimate system errors, which are then entered as corrections to the measurement data, ensuring their periodic correction. In the presented algorithm, the on-board systems provide full information about the location of the object (x, y) and its traveling speed (V_x, V_y).
In the complementary Kalman filter values: Δx, Δy, ΔV_x, ΔV_y are considered as state variables that shall be estimated. In addition, slow-changing GPS clock errors should be taken into account in the estimated state vector. In the three-dimensional coordinate system the position of the train is described by three coordinates x, y and z (for 2D digital maps z is not estimated). Additional unknown is the offset between the receiver clock and GPS time Δt. Therefore, determining the coordinates of the object requires measuring four pseudoranges and solving four non-linear equations (Kaniewski 2020; U.S. Dept. of Defense, 2020) in accordance with the relation (3).

$$\Psi_i = \sqrt{(X_i - x)^2 + (Y_i - y)^2 + (Z_i - z)^2} + c\Delta t \tag{3}$$

where: Ψ_I is measured pseudorange from the object to the i-th satellite for i = 1, 2, 3, 4; X_i, Y_i, Z_i are coordinates of the i-th satellite determined on the basis of a navigation message; x, y, z are coordinates of the object in the WGS-84 coordinate system; Δt is offset between the receiver clock and GPS time; c is the velocity of light.
The distance equivalent of the receiver clock offset $c\Delta t$ is modelled as an additional element extending the state vector $b(t)$. However, the single-state model of the GPS receiver clock errors is so different from reality that in most of the publications the authors propose a two-state model, which additionally includes the clock drift $d(t)$. The example of such a solution is shown in the block diagram (Fig. 3).
To estimate the state vector in such a system, a linearized Kalman filter can be used, which implements the following algorithm (Chrzan et al., 2019; Kaniewski, 2020):

a) Initialization of the algorithm: assignment of the initial estimate of the initial state of the filtration errors covariance matrix $\boldsymbol{P}(0/0)$ the values resulting from the assumed initial conditions model.
b) Time update stage: prediction of the state vector $\hat{x}(k+1|k)$ together with the covariance matrix of prediction errors $\boldsymbol{P}(k+1|k)$ based on estimate $\hat{x}(k|k)$ and filtration errors covariance matrix $\boldsymbol{P}(k|k)$ obtained in the previous calculation step and the process noise covariance matrix $\boldsymbol{Q}$:

$$\hat{x}(k+1|k) = \Psi\, \hat{x}(k|k) \tag{4}$$

$$\boldsymbol{P}(k+1|k) = \Psi\, \boldsymbol{P}(k|k) \Psi^{T} + \boldsymbol{Q} \tag{5}$$

c) Calculation of the measurement residues vector $e(k+1)$ and the covariance matrix $\boldsymbol{R}_e(k+1)$ on the basis of the prediction results $\hat{x}(k+1|k)$, $\boldsymbol{P}$(k+1|k), current measurement $\boldsymbol{z}(k+1)$ and the measurement errors covariance matrix $\boldsymbol{R}(k+1)$:

$$e(k+1) = \boldsymbol{z}(k+1) - \boldsymbol{H}[\hat{x}(k+1|k), k] \quad (6)$$

$$\boldsymbol{R_e}(k-1) = \boldsymbol{H}(k-1)\boldsymbol{P}(k+1|k)\boldsymbol{H}^T \cdot \cdot (k+1) + \boldsymbol{R}(k+1) \quad (7)$$

d) Kalman gain matrix calculation $\boldsymbol{K}(k+1)$:

$$\boldsymbol{K}(k+1) = \boldsymbol{P}(k+1|k)\boldsymbol{H}^T(k+1) \cdot \cdot R_e^{-1}(k+1) \quad (8)$$

e) Measurement update stage: estimation of the state vector $\hat{x}(k+1|k+1)$ together with the filtration errors covariance matrix $\boldsymbol{P}(k+1|k+1)$ based on the predicted estimate $\hat{x}(k+1|k)$, calculated measurement residues vector $e(k+1)$ and Kalman gain matrix $\boldsymbol{K}(k+1)$:

$$\hat{x}(k+1|k+1) = \hat{x}(k+1|k) + +\boldsymbol{K}(k+1)e(k+1) \quad (9)$$

$$\boldsymbol{P}(k+1|k+1) = =[\boldsymbol{I} - \boldsymbol{K}(k+1)\boldsymbol{H}(k+1)]\boldsymbol{P}(k+1|k) \quad (10)$$

where: $\boldsymbol{H}(k+1) = \left.\frac{\partial h(x)}{\partial x}\right|_{x=\hat{x}(k+1|k)}$ whose ij-th element is partial derivative of i-th element of nonlinear vector function $\boldsymbol{h}(*)$ in relation to j-th element of the state vector x, where the derivative is calculated at a point defined on the basis of the estimated object path. $\boldsymbol{I}$ denote an identity matrix.

The use of this model can lead to the significant reduction in the error of determining the position of objects.

4. The concept of using GNSS signal for train control

Operating on the railway route requires the installation of expensive railway traffic control devices, and then incurring expenditures on the servicing of devices as well as on the employees necessary to maintenance it. While it is economically justified on high-capacity railway lines, in the case of railways lines with local importance, technical solutions should be introduced to reduce operating costs. For example, for low capacity utilization railway lines it is possible to operate the trains using GNSS systems supported by on-board train devices.

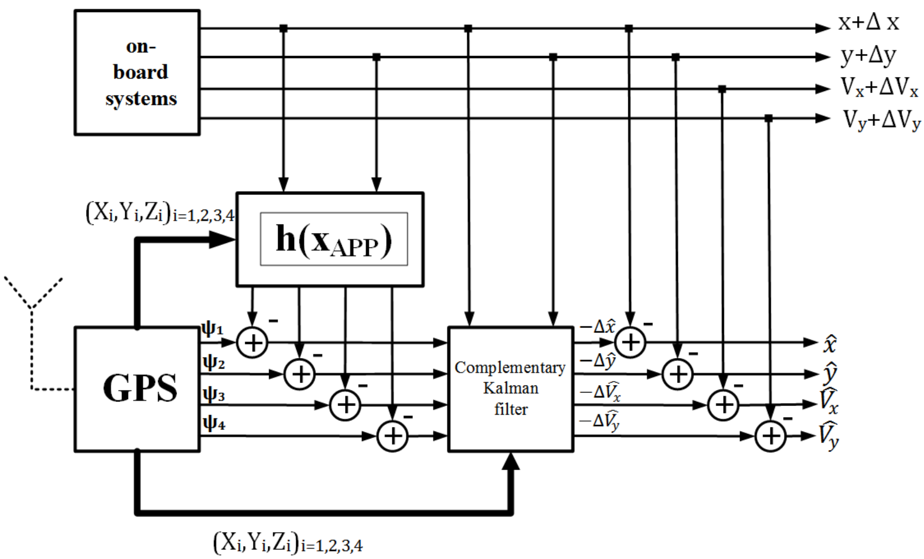


Fig. 2. Kalman filter in the on-board system cooperating with GNSS (Δx, Δy - positioning errors; ΔV_x, ΔV_y - speed measurement errors; X_i, Y_i, Z_i – the position of the i-th satellite determined on the basis of navigation message; Ψ_i - measured pseudorange from the object to i – of this satellite for i = 1, 2, 3, 4, $\hat{u}$- estimate of u value)

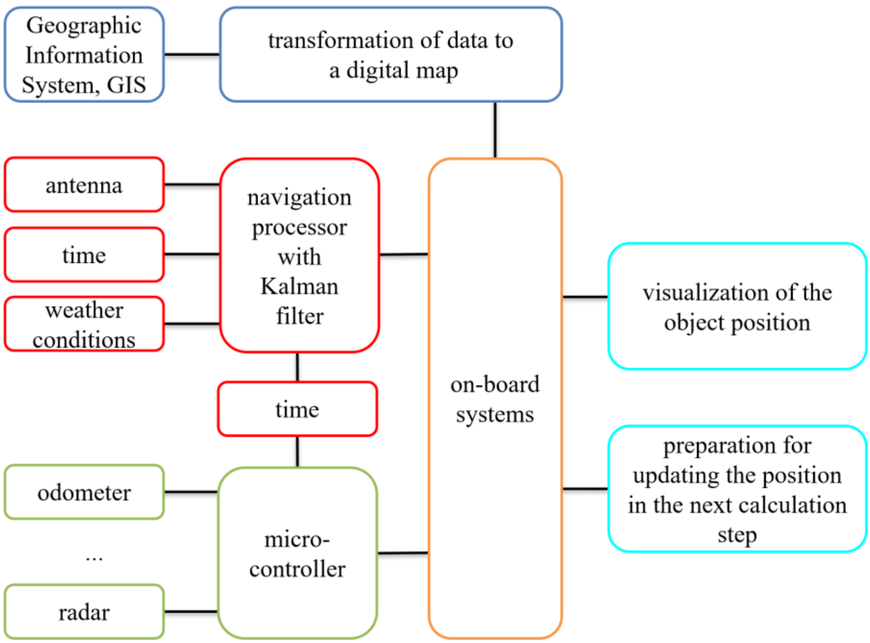


Fig.3. Block diagram of devices supporting the operation of on-board systems (the filter implementation is included in on-board systems)

Train operation on lines depends primarily on how the distance between trains traveling in the same direction is regulated. There are two ways of trains operation adjust:

– time interval working,
– safety distance operating.

In addition to the methods mentioned above, it is possible to adjust the headway between trains (the distance between trains; the front of the second and the end of the first) based on a braking distance. Then there are two modes of train operation control (Pan, et al. 2018):

– Relative Breaking Distance Mode (RBDM),
– Absolute Breaking Distance Mode (ABDM).

In the first train operation control mode, the distance between trains is:

$$h=s_{b2}-s_{b1}+m \tag{11}$$

where: h is headway, s_{b2} is braking distance of the second train, s_{b1} is braking distance of the first train, m is margin.

With ABDM the distance between trains does not depend on the braking distance of the first train. What is important is the braking distance of the second train. The distance between trains travelling in the same direction is then:

$$h=s_{b2}+m \tag{12}$$

where: h is headway, s_{b2} is braking distance of the second train, m is margin.

In the case of moving block signaling a headway is adjustable based on the precise, real time calculation of the speed, location and direction of each train. Necessary parameters should be determined as combination of data from several sensors e.g. markers along the track, speedometer, GPS with Kalman filter. It is obvious that such a system (Fig. 4) also requires continuous, bidirectional track-to-train data communications. On lines with a heavy traffic load, train-location and -integrity do not have to rely on trackside equipment (e.g. signals, track circuits or axle counters) but can be handled by trains and the Radio Block Centre (RBC). Such a solution, requires the railway line to be equipped with devices necessary for the 3rd level of ETCS and satellite navigation receivers (Kornaszewski et al., 2017).

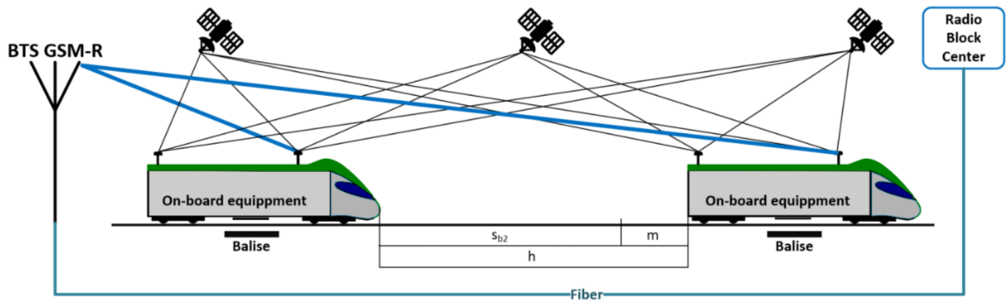


Fig. 4. The concept of the moving block signaling using GPS signals

Level 3 ETCS is a development of the ETCS Level 2 by transferring the track occupation control function from track-side to train. It enables train operating according to the principle of a moving block signaling and elimination of trackside equipment. Track data and position reports are transmitted using the GSM-R system. Additional implementing of GPS receivers will not only enable correction and verification of the position of the train, but will also perfectly improve the synchronization of radio transmission for the GSM-R subsystem.

The signal received from the GPS to the antennas installed on the front and the end of the train allows in this case to determine the position of these elements in relation to the railway route. The concept of train integrity control using this solution will be presented later in the paper. However, if we assume that the positioning error will be approximately 2m, then this is sufficient to control and supervise the movement of the train in the direction of travel. Of course, at this level of assumed accuracy it is difficult to determine whether the train is moving on the right track, but other cooperating devices e.g. balises could determine vehicle's location and direction of movement. If the GSM-R is used to exchange information between vehicles and RBC, then the railway traffic can be conducted depending only on the distance between two trains running in the same direction (called headway). If we assume the worst-case scenario with a poor visibility of satellites, positioning error can reach 20m, so to ensure enough breaking distance in every case an additional margin should be adopted. Knowing the characteristics of the train (e.g. its mass, speed, the braking characteristics) and the characteristics of the line (e.g. line speed, gradient), and assuming devices delays and driver reaction time "safe zone" could be calculated.

In order to increase the accuracy of positioning train on the route, it is possible to use an enhanced variant of the GPS - Differential Global Positioning System (DGPS). However, it requires the construction of reference stations that would correct the positioning errors vector.

5. The use of satellite technology for positioning defects in diagnostic tests of rails

5.1. Determining the position of the ultrasound railroad testing car

The concept of construction and implementation for operation of the ultrasound railroad testing car into service (Fig. 5) was developed in the 90s of the last century. It was caused by the necessity of conducting mass tests of rails, which in turn required a specific measurement speed. The first version of the ultrasound railroad testing car as well as further development versions were created at the Faculty of Transport, Electrical Engineering and Computer Science, Casimir Pulaski Radom University (Ciszewski, 2007).

Due to the subject of the paper, only the functionality of the system for determining the position of defects in the rails with the use of satellite technology will be discussed.

Frequency of refreshing location measurements in the applied GNSS receiver is 1Hz, which causes a significant problem of determining the position of the automatic testing car between consecutive measurements.

Because during the tests the railroad testing car is in motion with a typical test speed of about 10 m/s, despite the relatively high precision of determining the position (0.7-2m, DGPS) between subsequent position readings, the testing car moved to a significant distance (about 10 m) and the resulting measurement errors far exceeded the errors of reading the GPS position. For this reason, the simple method of position interpolation has been developed to determine the position of equipment between the individual readings.

Fig. 5. Ultrasound railroad testing car (Ciszewski, 2007)

A necessary condition for correct interpolation is the large inertia of the vehicle. In the case of railway vehicles, this condition seems to be met. During the tests, two polynomial interpolation methods (zero and first degree) were tested. In simpler method it was assumed that in sections between consecutive measurements the railroad testing car moves all the time with the last read speed (hence the requirement of inertia). The change of location on the route is then determined by projecting the travelled distance Δs (13) into the graph showing the route:

$$\Delta s = V_i t \tag{13}$$

In the second method, the last two speed reads were taken into account. The next one is determined from the linear dependence of the last two speed reads. In this case, the new speed is determined from the dependence (14):

$$V_{i+1} = \frac{V_i - V_{i-1}}{t_i - t_{i-1}}(t_{i+1} - t_{i-1}) + V_{i-1} \tag{14}$$

The current covered distance is obtained by calculating numerical integral of the speed function over the time (15):

$$\Delta S = \int_{t_i}^{t_{i+1}} V(t)dt \tag{15}$$

As before, the change of location on the route is then determined by projecting the individual travelled distances into the graph showing the route.
Due to the high inertia of train at the tested measuring speeds (up to approximately 50 km/h), both methods give similar results in practice.

5.2. Determine position of defects in the rails in manual ultrasonic testing

Diagnostics using automatic ultrasound railroad testing car for flaw detection of rails in the track is just one of the methods used by infrastructure operators. Another commonly used diagnostic technique is non-destructive defectoscopic examination performed by using ultrasonic flaw detectors on trolleys (Fig. 6). The "performance" of a single diagnostic flaw detector on trolley is typically from 6 to 9 km of rail per day.
In typical situation devices are used to diagnose defects in rails, but the diagnostic team is responsible for determining the position of the defect on the route. Equipping the diagnostic trolley with satellite receivers and using them as a source of determining the position of defects (Fig. 7) allows for significant simplification and acceleration of the procedure for determining the flaw location in track.

6. The concept of satellite method for determining track spatial orientation

Problems with the accuracy of determining track spatial orientation can be eliminated or reduced due to the support of satellite systems and the use of the Kalman filtration considered above for the estimation of measurement results. This approach allows to determine the spatial orientation based on measurements of phase differences of signals induced in several receiving antennas, located in a specific spatial configuration. For example, in the ultrasound railroad testing car, it enables the integration of the above-described ultrasonic diagnostic tests with determining track spatial orientation.
Figure 7 shows an excerpt from measurements on the section of line 22 between Wolanów railroad station and Przysucha station. The numbered points in the figure indicate the locations where defects were recorded in one of the rail tracks using GPS technology.

(a) (b) (c)

Fig. 6. Measurement of the rail by a defectoscopic trolley a) without GPS correction, b) view of the antenna on the measuring trolley, c) measurements with correction on the railway route

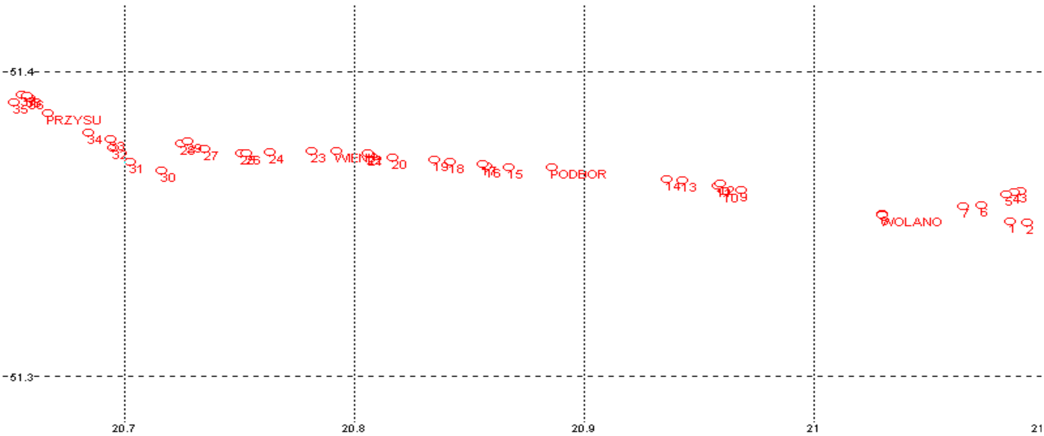


Fig. 7. Sample measurement of the defect location using a GPS receiver and a defectoscopic trolley equipped with the Metrison DI60 flaw detector

As mentioned above, the measurement concept is based on phase shift of signals transmitted by the satellite and received by two apart antennas. This value in relation to the distance between antennas is proportional (16) to the angle between the lines formed by these antennas and the line formed by the antenna and the satellite (Fig. 8):

$$d\varphi_a^k = \boldsymbol{S}_a^k \boldsymbol{X}_a - N_a^k + \vartheta_a^k \quad (16)$$

where: $d\varphi_a^k$ is phase difference of signals induced in antennas, defining the base a, from the satellite k; $\boldsymbol{S}_a^k$ is unit vector lying on the straight satellite-antenna; $\boldsymbol{X}_a$ is base vector (vector between antennas); N_a^k is number of occurrences of periods (length) of carrier wave; ϑ_a^k is interferences occurring in the transmission channel and noises of the receiving subsystem. Calculation of the above angles (at least from two satellites) allows to determine the values of the roll, yaw and pitch angles of the segment formed by the antennas (at least three) used for measurements. Installation of the antenna arrangement and the specialized receiver of satellite signals on the board of the ultrasound railroad testing car, allows to determine the angles roll, yaw and pitch angles of the rail track.

In current solutions, determination of spatial orientation based on indirectly measured distance difference (Fig. 8) using a known distance between antennas $||\boldsymbol{X}_a||$ „base" and the unit vector of the $\boldsymbol{S}^k$ satellite is realized by minimizing the sum of squares of the quality function values:

$$Q(\boldsymbol{A}) = \sum_{a=1}^{m}\sum_{k=1}^{n}\left(\Delta D_a^k - \boldsymbol{X}_a^T \boldsymbol{A} \boldsymbol{S}^{\boldsymbol{k}}\right)^2 \tag{17}$$

where: ΔD_a^k is the distance difference between the antennas forming the a base to the k satellite; m is the number of bases used in the process; n is the number of satellites used in the process; $\boldsymbol{X}_a^T$ is base vector (between antennas) described in the coordinate system associated with the object; $\boldsymbol{S}^{\boldsymbol{k}}$ is satellite unit vector described in the local horizon coordinate system
$\boldsymbol{S}^{\boldsymbol{k}}= [S_x; S_y; S_z]^T$; $\boldsymbol{A}$ is transformation matrix of spatial orientation from the coordinate system of the local horizon to the coordinate system associated with the object.

Currently used implementations of the process of determining spatial orientation using signals from the GPS system are based on repeated measurements and determining on their basis the average values of the angles of the roll, yaw and pitch angles (Fig. 9). It follows that the reduction of errors is done in the process of solving the task of determining angels of the roll, yaw and pitch angles, and not at the stage of signal processing.

Therefore, it makes sense to apply solutions in the field of processing signals received from satellites, enabling reduction of interference related to the propagation of electromagnetic waves and errors occurring in the measurement process, in order to improve accuracy and increase the dynamics of determining the track spatial orientation. Therefore, it is rational to use the Kalman's filtration in the system shown previously in Figure 3.

The simulation in Matlab gives results for left and right rail, which are shown in Fig. 10 a, b.

With the change of wheel-rail friction coefficient, the average wear rate of outer wheel tread of wheelset three is 49.52% and the wheel flange is 0% and the wheel back is 100%.

7. GNSS based train integrity control

The method of train integrity control presented in the paper consists in real-time analysis of satellite signals coming from two navigation receivers (Chrzan et al., 2019; Duan et al., 2022; Makowski et al., 2016). One of them is placed at the front and the other at the end of the train (Fig. 11).

Signals from the navigation system receivers are transmitted (e.g. using the Wireless LAN) to the processing and logging device (located in the train driver's cab), which determines the current positions of the receivers. The train driver has the possibility to check the train integrity in real-time on the basis of information displayed on the screen. In addition, data from the processing and logging device could be transmitted to the external systems using available transmission media, e.g. to railway operation control center using GSM-R. The structure of the train integrity control system is shown in Fig. 12.

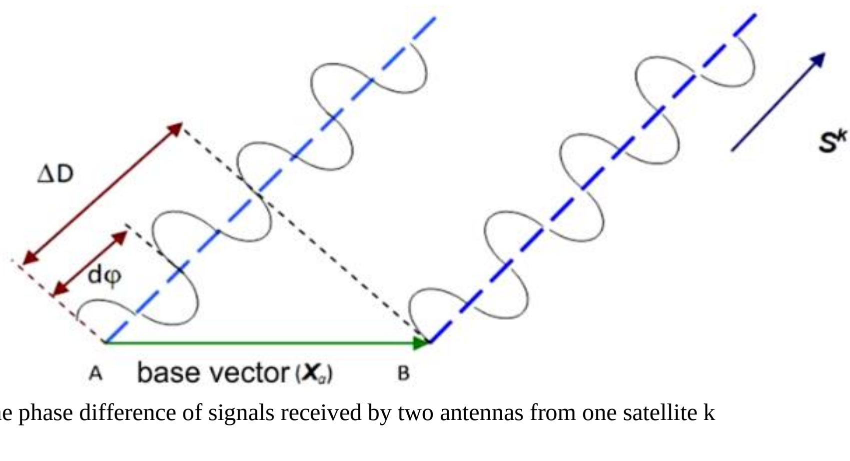


Fig. 8. The phase difference of signals received by two antennas from one satellite k

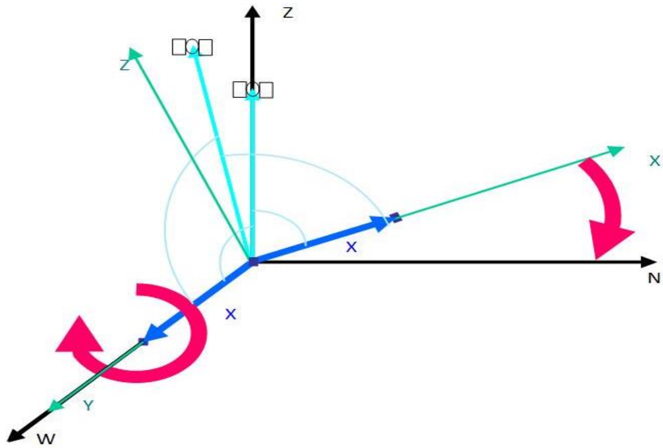
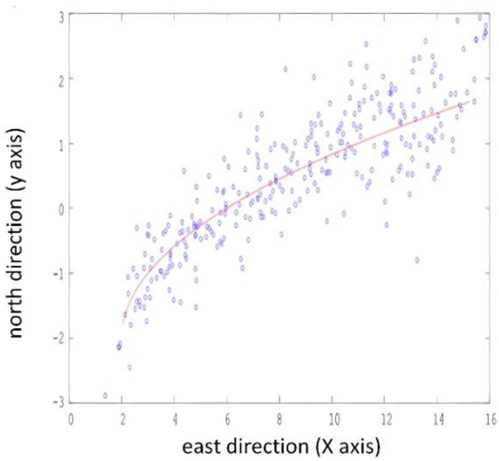


Fig. 9. Physical interpretation of the process of the classic method of determining spatial orientation

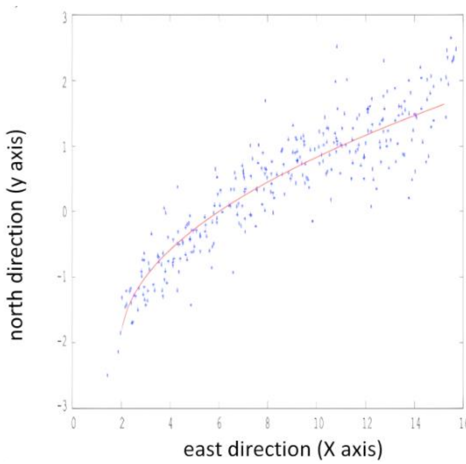
On the basis of the determined positions of the receivers, a distance between them (d) is calculated. It is assumed that this distance is constant both during train running and at standstill. Determining the distance between GNSS receivers is subject to an error related to inaccuracy of positioning these receivers. Conducted simulation and field tests allowed to determine the maximum value of GNSS receivers positioning error, which in Fig. 13 was marked with the letter (b). The determined distance between GNSS receivers should not exceed the sum of the original distance between them (d) and the assumed maximum positioning error (b).

The concept takes into account the case in which distance between GNSS receivers (d) may be reduced while a very long train is running on the track in curve. In such case system does not warn about lack of train integrity.

The analysis of positioning errors and the use of the Kalman filter for the estimation of measurement results (Chrzan et al., 2019; Makowski et al., 2016) is the important aspect that has been pointed out in the paper. This approach allows to improve the accuracy of positioning GNSS receivers placed at the front and the end of the train, which is the basis of the above-mentioned method.



(a)



(b)

Fig. 10. Simulation results a) left rail b) right rail

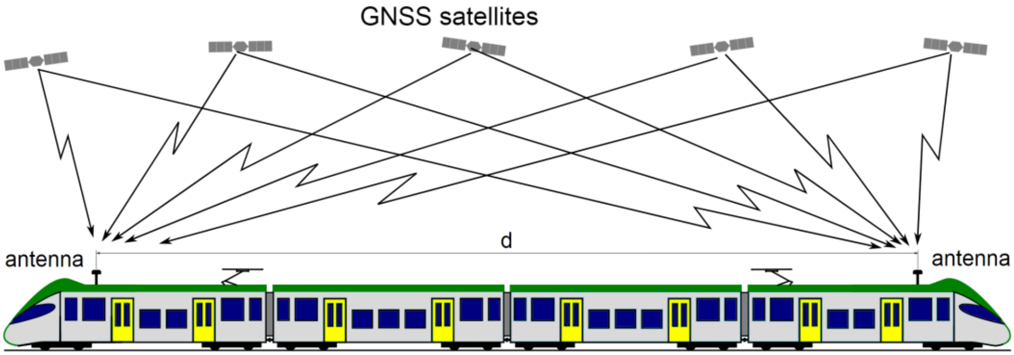


Fig. 11. Determining the train length based on GNSS signals (Chrzan et al., 2019)

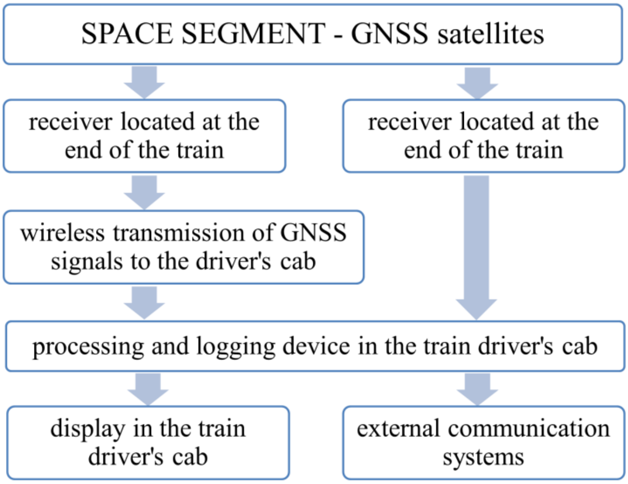


Fig. 12. Structure of the train integrity control system (Chrzan et al., 2019)

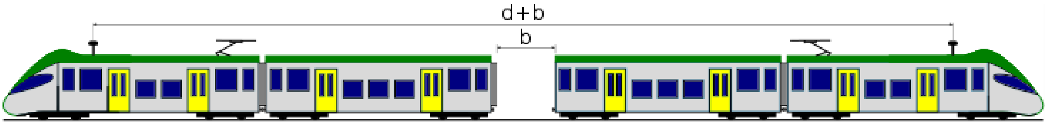


Fig. 13. The moment in which the train separation was detected (Chrzan et al., 2019)

8. Conclusions

Global Navigation Satellite Systems (GNSS) are used in various modes of transport, including rail transport. Main application include train location, fleet and route management, passenger information and safety management. However, it should be noted that when using this technology for rail traffic control, the level of dependability of the determined train position, referred as position integrity, is very important because it affects to traffic safety. Typically, a combination of different methods is used to ensure an adequate level of accuracy, which most often integrates data acquired from various GNSS systems as well as additional sensors (e.g., inertial - accelerometers, gyroscopes). The Kalman filtering is one of the method that allows to integrate data from multiple sources. The use of Kalman filtering in GNSS satellite receivers improves the accuracy of moving objects positioning e.g. trains or railway infrastructure elements. The features of the Kalman filter make it an optimal estimator for the applications presented in the paper: automatic train movement, determine of defects' location in rails, track spatial orientation measurement, as well as train integrity control. The use of Kalman's filtration, presented in the paper, shows that it is the universal method improving estimated measurement parameters and can be used in many applications of satellite systems for railway tasks. Since railway traffic control systems are safety-related systems, it is necessary to carry out a risk assessment process to estimate the safety integrity level (SIL). However, determining SIL for these types of GNSS applications can be very complex. This is due to many different reasons, for example, the accuracy of GNSS positioning may vary depending on factors such as the number of visible satellites, weather conditions, terrain obstacles, etc. Therefore, SIL assessment should be carried out individually for a specific system and context of its use.

The development of the author's method of using GNSS systems to determine the continuity of a train and to determine the position of defects in railway rails has allowed the defect wagon to improve the efficiency and accuracy of defect detection and, in the case of train continuity control, to increase the safety of rail transport. In the article, the authors presented an original approach to known solutions used in satellite technologies, directing them towards railway tasks, which allowed the development of unique solutions in different areas of railway safety

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