Train-based location by detecting rail switches

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Abstract

The train-based identification of topological and topographic characteristics of the rail track—i.e. rail switches, crossings—represents an important component of future location systems in guided traffic. For this application, robust sensors capable of working under adverse conditions (e.g. dirt, rain, snow) are needed. Eddy current sensors are completely insensitive to these influences. Such sensors are already part of a newly developed system for slip-free speed and distance measurement of rail vehicles by transit-time correlation. The additional use of these sensors to detect switches is a very interesting novel approach, both from a technical and economic point of view.

The aim of this paper is to outline the strategy for detecting rail switches. In this context, typical signals are discussed. Furthermore, suitable signal processing and pattern recognition methods for detecting rail switches are presented. Based on signals obtained by field tests in cooperation with the German railway authority Deutsche Bahn AG, the performance of the proposed methodology is demonstrated.

1 Introduction

Present systems for locating rail vehicles depend on installations along the track, e.g. balises and axle counters. More advanced navigation systems as the Global Positioning System (GPS) depend on a highly complex satellite system; in [1] it is shown that multipath propagation and shadowing of radio waves (as in tunnels!) are the reasons that GPS systems alone cannot position land vehicles continuously. Therefore complementary systems are needed. From a systems point of view, a completely train-based system would be highly desirable.
In [3], the concept of a digital rail map is presented. Its basic idea is to base train location on topological information of the rail network. The nodes in this network represent rail switches and crossings. If these can be detected unambiguously, rail vehicles can be located to an accuracy between those nodes; conventional odometry based on integrating vehicle speed can then be used for interpolation between nodes. To detect rail switches, various physical sensor principles are conceivable: microwave radar, optical systems and inductive sensors.

In the following, results obtained with eddy current sensors will be presented. This sensor principle was felt to be most promising concerning robustness against adverse weather and environmental conditions. These sensors were developed for a slip-free speed and distance measuring system; they are described in a companion paper [4] in this conference.

In Section 2, the basic principle is explained. Section 3 presents the characteristics of signals obtained from eddy current sensors. Section 4 then outlines the detection, classification and identification of individual rail switches and other rail components. The main result is that the system proposed is completely autonomous and does not need any installation outside the train; it is able to locate the train with high reliability and with an accuracy that might come down to the sleeper distance.

### 2 Switch detection principle

Fig. 1 shows the schematic set-up of a train-based switch detection system. By means of suitable sensors, inhomogeneities along the track (e.g. rail clamps and other components in the area of the rail) are registered. The shape of the resulting signals depends on the physical sensor principle as well as on the sensor position above the rail, and on the inhomogeneities arising along the track. The main idea of the switch detection is to capture characteristic signals of the different components in the area of switches (guide rails, switch blades, diamond crossings etc.); see Section 3.

![Figure 1: Measuring system to detect rail switches.](image)

To detect switches, at least one sensor signal \( s(t) \equiv s_1(t) \) is necessary, which, however, has to be converted to a speed independent representation \( s(x) \) with \( x = \)}
Figure 2: Sensor signal $s(x)$ obtained when passing over a switch in the branch track position.

$\int v(t) \, dt$. This scaling requires a precise estimate of the speed $v(t)$, which can be obtained by a transit-time correlator, for example; see Engelberg & Mesch [4]. For this purpose, a further sensor is placed at a distance $l$ to the first one in the direction of motion. This sensor can, of course, also be used for detection so that the quality of the measured signals—and, thus, the detection results as well—is enhanced by means of sensor fusion techniques; see Luo & Kay [7]. By using more sensors placed across the track width, different relevant areas of the track can be simultaneously “observed”—e.g. both rails as well as the central area between them, in which for example when passing over switches the rails of the branch track can be detected.

As will be shown, the signals obtained from the eddy current sensors significantly depend on the magnetic “events” along the track. As switches are concerned, they depend on the switch setting, on the switch type, and on the individual switch. Therefore, proper processing of the signals comprises the following steps:

- detection (decision whether an event exists),
- classification of the type of event, and
- identification of the individual event.

If these informations are stored in a digital rail map in proper form, a comparison with the signals in the block “pattern recognition” (Fig. 1) gives the relevant location result $r(x)$.

3 Characteristics of the sensor signals

The type and size of the irregularities that can be detected by the sensors in the area of the rail mainly depend on the distance $z_0$ between the sensor and the rail edge. For safety reasons, $z_0 > 80 \text{ mm}$ must be chosen. In this case, the eddy current
sensors only register coarse inhomogeneities, i.e. mainly the rail clamps. In the area of switches, metallic components of the switch (e.g. guide rails) are detected as well.

In Fig. 2, a typical switch is depicted; see Berg & Henker [2]. First, we will consider a signal $s(x)$ that was obtained by a sensor passing over the rail marked grey in the branch track position. The area of the switch blade can be distinguished in the signal, because here the branch track rail typically consists of some additional metallic components—such as elements to support the switch blade [2]. The area of the guide rail is clearly evident in the sensor signal as well. The increase of the signal amplitudes registered here is mainly due to the parts used to fix the guide rail (elbows and screws), which partly surmount the top edge of the rail. The guide rail itself can barely be recognized in the signal of a differential sensor, if its electromagnetic properties are homogeneous, as the differential eddy current sensors only detect non-uniformities [4]. In the area between the switch blade and the guide rail only the rail clamps affect the sensor signal; mostly there are no further prominent components in this section of the switch.

Fig. 3 shows schematically the signal $s(x)$ obtained when passing over a switch in the main track position. In the signal, the point of the switch blade, a reinforcement [2] as well as a diamond crossing can be distinguished. Compared to the signals registered in the branch track position discussed above, it is obviously different. Consequently, the switch setting can be extracted from the respective signal patterns.

In Fig. 4, an example of the signal recorded when passing over a crossing switch [2] is depicted. A guide rail, the central area of the switch (consisting of two switch blades) as well as a diamond crossing form in this case the sensor signal $s(x)$. The different signals obtained from normal rail clamps and components
of switches (guide rails, switch blades, diamond crossings etc.) allow a detection of these individual components, as discussed in the next section.

4 Signal processing and pattern recognition

4.1 Overview

A robust system capable of detecting rail switches requires the signals $s_i(t)$ to be transformed to a speed independent representation $s_i(x)$ by means of a proper scaling device; see Fig. 1. For this purpose, the signals $s_i(t)$ are limited to a cutoff frequency $f_c(v)$ with an adaptive anti-aliasing filter. Subsequently, the filtered signals are sampled with the frequency $f_s(v) = f_o \cdot v(t)$, where $f_o$ denotes the spatial sampling frequency of the resulting signals $s_i(x)$. Due to the limited spatial resolution of the sensors used, the choice of a sampling frequency of $f_o = 30 \text{ m}^{-1}$ has proved to be absolutely sufficient in practice to enable a reliable recording of the interesting individual characteristics of the rail track.

As already stated in Section 3, the signals obtained by the eddy current sensors show significantly higher amplitudes when passing over certain components of rail switches than in the case of normal rail clamps. The next subsection concerns a method that permits to detect such track events in the measured signals, and to assign them to the respective classes of switch components based on the signal characteristics. To determine the location of the vehicle, the list of the rail switches detected during its route is compared with the information about the network topology stored in the digital rail map by means of graph matching techniques; see Liedtke & Ender [6]. In this case, the graph search can be substantially
s_i(x)

rectification → sensor fusion → lowpass → threshold → feature extraction → classification → r(x)

Figure 5: General strategy to detect rail switches.

simplified by incorporating knowledge about the route available a priori.

However, to enable an identification of individual rail switches, the digital rail map has to be extended: Features describing each switch are required, i.e. for each individual switch a kind of "fingerprint" has to be stored additionally; see Section 4.3. In this case, the location task becomes easier than in the case of searching the network graph.

Finally, in Section 4.4 a simpler alternative to determine the train location based on tracking any track components that can be captured by our sensors—especially rail clamps—will be presented.

4.2 Switch detection and classification

The general strategy used to detect rail switches is based on the analysis of the envelope of the sensor signals s_i(x); see Fig. 5. For this purpose, a rectification of the signals is performed first. If several similar sensors are placed closely behind each other in the direction of motion, as in our experimental configuration according to Fig. 1 (l = 0.2 m), it is straightforward to carry out a fusion of the corresponding sensor signals. The simplest way to realize such a fusion is by averaging the rectified signals. By choosing a suitable distance l between the sensors, the result obtained will show a notably smoother behaviour than the sensor signals, whereas the interesting events will feature high positive amplitude values. To detect these events, a lowpass with cutoff frequency f_{LP} is applied in combination with a threshold γ; see Fig. 5. Note the analogy between this methodology and the matched filter with respect to the envelope used in signal detection. The threshold value γ is determined adaptively based on the empirical standard deviation σ of the zero-mean sensor signals according to the equation γ := c · σ. If the parameters f_{LP} and c are properly chosen, the detected segments of the resulting binary signal will indicate the location of the events sought after. Thereafter, geometrical features—such as location, length and distinctness—of each segment are extracted and utilized as input parameters for the classification process, i.e. the assignment to the respective component classes. In a further processing stage, context sensitive methods (graph matching, among other things) are employed to group the single events to different rail switch types [6]. Alternatively, the envelope signal obtained after the low-pass filtering could be immediately used for a classification, for instance by means of correlation techniques.

As an example of the strategy proposed, Fig. 6 shows a measured signal s(x) containing different features of the rail. The "boxes" overlaid indicate the detection results. Especially, at the position x = 34 m a rail joint has been detected,
4.3 Switch identification

The characteristic arrangement of components in the area of rail switches allows an identification of individual switches. For this purpose, the digital rail map has to be extended by adding “sample signals” \( w_i(x) \), each one of them representing an individual rail switch at a specific setting. If a typical switch length of 40 meters is assumed, on the average 1,200 sample values are needed to represent a switch. Thus, more than 300,000 such signals can be stored on a conventional CD-ROM without compression. Though the expense of recording each existing switch is substantial, this procedure can be widely automated with the method described in Section 4.2.

The actual rail switch identification is based on correlating the signals \( w_i(x) \) of all switches in question with the sensor signal \( s(x) \). If a certain switch \( i \) is contained in the measured signal \( s(x) \), the cross-correlation function \( \rho_{sw}(x) := s(x) \otimes w_i(x) \) will show a distinct peak indicating the position of the switch. This peak can be detected by means of a threshold. To calculate \( \rho_{sw}(x) \) in real time, 4.5 millions arithmetical operations must be performed each second, if a speed of 100 \( \frac{m}{s} \) and switch lengths of 50 m are assumed. Although these requirements can be easily fulfilled by modern processors, it is still necessary to restrict the amount of switches coming into question. Thus, additional knowledge—for example in the form of the digital rail map, the detection results according to Section 4.2 as well as of a rough estimate of the train location—has to be exploited.

Fluctuations of the sensor distance \( z \) to the rail edge cause a nonlinear distortion of the measured signal \( s(x) \). This leads to a lower correlation between the signals \( s(x) \) and \( w_i(x) \), because the cross-correlation function only registers the linear dependency between two signals. However, experiments have demonstrated that even in the case of large distance fluctuations (\( \Delta z = 20 \text{ mm} \)) a reliable detection is possible, and the correlation function still shows a distinct maximum with \( k \approx 0.9 \).

Fig. 7 shows an example of the switch identification. In the measured signal \( s(x) \), a rail joint is present at the position \( x = 53 \text{ m} \); from the position \( x = 100 \text{ m} \) on, a switch blade can be recognized. In an earlier measurement campaign, the same switch had been recorded and stored in the database as the “sample signal” \( w(x) \). At the bottom of the figure, the cross-correlation function \( \rho_{sw}(x) \) is de-
picted, the pronounced maximum of which ($k = 0.99$) marks the position of the detected switch.

4.4 Detection of rail clamps

The events detected by the eddy current sensors—i.e. essentially rail components such as rail clamps—can be used for measuring the distance covered by the rail vehicles as schematically shown in Fig. 8. The estimated distance $\hat{x}$ is given by the equation

$$\hat{x} = \sum_{i=1}^{E} \Delta x_i ,$$

where $\Delta x_i$ denotes the distance between two consecutive events, and $E$ the number of detected events. Especially on straight tracks, $\Delta x_i$ corresponds to the distance between two neighbouring rail clamps, which is approximately 600 mm on modern main lines. However, this knowledge can only be used as a rough estimate for location purposes. To achieve more precise results, all individual distances $\Delta x_i$ should be determined and stored in the digital rail map [3]. Problems with this method may arise in case of false detections or undetected events—for example, due to changes of the rail track or to additional metallic parts, if these are not registered in the digital rail map. Consequently, additional efforts are necessary to ensure that reproducible results will be obtained.

Fig. 9 shows results of the detection of track events obtained during field-tests carried out on main lines of the German railway authority Deutsche Bahn AG. The
relative detection errors

\[ \delta_i = \frac{E_i - \bar{E}}{\bar{E}} \quad \text{with} \quad \bar{E} = \frac{1}{M} \sum_{i=1}^{M} E_i \]  

are plotted for \( M = 12 \) tests in two different track sections A and B. The diagram shows that the detection errors are smaller than 0.12% in all cases. The measured mean distance between two neighbouring events was approximately 0.6 meters, which corresponds with the nominal distance between two adjacent rail clamps.

To improve the performance of this method, false detections could be avoided by incorporating additional available information. For instance, it is straightforward to estimate the current speed according to

\[ \hat{v} = \frac{\Delta x_i}{\Delta t_i}, \]  

where \( \Delta t_i = t_i - t_{i-1} \) denotes the time interval between the detection of two events. In practice, the speed \( v \) is subject to smooth variations due to the limitations in acceleration and deceleration of the rail vehicle. Since the measurement of the transit time \( \Delta t_i \) can be done with high accuracy, changes of speed which are physically not possible could be recognized as detection errors. Furthermore, since rail clamps can be detected on both rails, sensors could be placed on both sides of the vehicle. The resulting signals could be combined by means of sensor fusion strategies [7].

5 Conclusion

The methods presented in this paper to detect track events (e.g. switches, rail joints as well as artificially coded patterns) have proved in our preliminary experiments to behave very robustly. Since these techniques do not require necessarily the track to be modified, they represent a very interesting approach for future location systems, both from a technical and economic point of view. Moreover, additional
applications in the context of rail vehicles are conceivable. As an example, the analysis of the signals could be employed to detect coarse rail defects—such as cracks of the rail head—during train operation.

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References


