An innovative algorithm for train detection

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I. ABSTRACT

Train detection is a very important research issue affecting vehicles and line safety. Currently, the European Train Control System ETCS (a signalling, control and train protection system) Level 1 and 2 provide the train localization functionalities by using track circuits and/or axle counter systems: the problem of these solutions is represented by the high cost of track circuit and axle counter installation and of the related equipment management. This paper presents an innovative train detection algorithm, able to perform the train localization, by estimating its speed, crossing time instants and axle number. The aim of the proposed solution is to use the same processing approach to evaluate all these quantities, starting from the knowledge of the vertical loads on the sleepers directly measured on the track. The inputs are processed through cross-correlation operations to extract the required information in terms of speed, crossing time instants and axle counter. A suitable model of railway vehicle and track has been also developed to test the algorithm when experimental data are not available. The railway vehicle chosen as benchmark is the Manchester Wagon, implemented in the Adams VI-Rail environment. The physical model of the flexible track has been implemented in the Matlab and Comsol Multiphysics environments. A simulation campaign has been performed in order to verify the performance of the proposed algorithm, under different operative conditions. The research has been carried out in cooperation with Ansaldo STS and ECM.

II. INTRODUCTION

With the increase of the vehicle speed and traffic in the modern railways, a safe signalling system is fundamental to ensure the safety and reliable railway services [1]. In particular, the main safety properties of a reliable signalling system are the train detection, railway traffic monitoring and speed control on the track behind to manage its movement according to the position of the train in front [2][3]. Track circuits and axle counters have been widely used to implement the train detection phase. Track circuits refer to a electrical circuit with a power unit at one end of a section track and its functionality is based on the state of the receiver: when the signal arrives at the receiver, the complete circuit is close and becomes in the energized state [4][5]. Otherwise, when a train is present, wheels shunt the track circuits and the receiver is de-energized. With the introduction of the electrification in railways, the rail are used both as track circuit, both and to carry the traction return current. To avoid interference, the power source of the track circuit uses a different shape from that of the traction supply and so a electromagnetic interference (EMI) is almost inevitable. For this reason, the axle counter have been widely used, as alternative to the common track circuit. Axle counters do not rely on a physical closed electric circuit, but consist of a pair of electromagnetic coils mounted on either side of the rail head [6][7]. However, as the operation hinges on the delicate changes of magnetic field [8], EMI remains to be a genuine concern for the reliable operation of axle counters. For this reason, many recent research works in literature propose a new simple sensor technology, the fiber Bragg grating sensor [9][10], to be free from the EMI interference problem and to enhance the accuracy and reliability of train detection and hence provide the signalling system with better safety assurance [11][12]. With the technique in optical fiber, any change of the shape of the profile of the wheel, also due for example to deterioration of the wheel/rail contact is not a source of uncertainty. With this innovative technology, the complexity of the measure system has moved from the sensor part to that of peak reading in the received signal. Chu-liang Wei et.al [13] have developed the X-Crossing and D-Crossing algorithm to compute the number of train axles crossing the measurement station: they have used a cut-off threshold followed by a derivative operation, to extract the useful peak corresponding to the crossing train axles from the received signals. T.K. Ho et.al [14] make the decomposition of the received signals in different frequency band with the Wavelet Transform to study and define the spectral characteristics of the useful signal. Buggy et.al [15] make use of cut-off thresholds and derivative operation to implement the axle counter function. In this scenario, the studied work is collocated. The proposed train detection algorithm has the aim of providing the localization of the train, in terms of speed, crossing time instants and axles number estimation. The formulation of the algorithm is quite general and it can be customized for several track measurement in inputs (vertical loads on sleepers, stresses, strains, etc). Consequently it can be employed in different typologies of measurement stations: in the work case the chosen input is the vertical load on the sleeper [16]. The novelty of the proposed algorithm is that it is based on a main method (cross and auto correlation of the input signal) to evaluate the train parameters as its axles number, speed and crossing times on the sleepers. Another important characteristic of the proposed method, that highlights its novelty respect others works in literature, is its robustness at different measurement chain performances (different signal-to-noise ratio of the input signal). A suitable model of railway vehicle and track has been also developed to test the algorithm when experimental data are not available [17][18][19]. The considered railway vehicle is the Manchester Wagon [20], implemented in the Adams VI-Rail environment. The physical model of the flexible track has been validated by means of the experimental data provided by Ansaldo STS and have been implemented in the Matlab and Comsol Multiphysics environments. Starting from the input
signal, the estimation algorithm uses the cross-correlation, to compute the crossing time instants of the train axles on the sleeper and consequently the vehicle speed; then, an operation of maximum peak detection, followed by a time filtering through a cut-off threshold has been implemented to realize the axle counter function. All the post process operations are based on the cross-correlation and this represents a point of novelty of the proposed method. To test the algorithm performance, a series of simulation campaign with different vehicle weight, speed and noise level on the input signal has been made. The research has been carried out in cooperation with Ansaldo STS and ECM.

III. GENERAL ARCHITECTURE OF THE MODEL

The architecture of the train detection algorithm (Fig.1) is composed of two parts: the physical and estimation model. The input of the estimation model can be classified into two types: experimental data measured in the real railway track or, in absence of them, data provided by a physical model. The purpose of this arrangement consists in the possibility of testing the algorithm performance, even when experimental data are not available.

![General architecture of the model](image1)

The physical model of the railway track consists of two sub-systems (see 2): a multibody model of the vehicle (in this case the Manchester Wagon [20]), implemented with VI-Rail software and a finite-element model of the flexible railway track, developed in Comsol environment. This two models interact through a global contact model, developed by the authors in previous works [17][18]. The architecture of the physic model is represented in Fig.2. At every time integration step, the multibody model evaluates the kinematic variables (position, orientation and their derivatives) of each wheel: at the same time, the finite-element model of railway track evaluates the position, orientation and their derivatives for the rail. Both the kinematic variables are then sent as inputs to the global contact model, that returns the global contact forces to be applied to the models. Once obtained the vertical forces on the sleepers, the estimation part begins. It is composed by two phases (both implemented in Matlab): the first of one computes the auto correlation of every input signal coming from the sleepers and the cross-correlation between every pair of input signal. The second phase, instead, aims to elaborate the signals previously obtained to determine the vehicle parameters as speed, crossing time instants on the sleepers and finally the number of train axles. The signal processing operations used in the second phase will be clarified in detail in Chap. V.

![Vehicle track and contact models](image2)

IV. PHYSICAL MODEL OF THE RAILWAY TRACK

In order to generate suitable simulation campaigns to test the proposed algorithm when experimental data are not provided, a model involving all components of the track structure and vehicle parameters is required. The response of the rail track system is investigated taking into account the infrastructure system, considering the interaction between rails, sleeper and ballast. The physical model consists of a 3D finite element model of the infrastructure (rail, sleepers and ballast), a 3D multibody model of the vehicle ([21]) and a contact model describing the interaction between the vehicle wheels and the rail. The vehicle model and the infrastructure model interact online during the simulations by means of a 3D global contact model, specifically developed to improve reliability and accuracy of the contact points detection. In particular the adopted contact model is based on a two step procedure; the contact points detection [17], [18] and the global contact forces evaluation [22]. The model (for further details one can see the previous bibliography references) can provide as outputs different track measurements signals like vertical loads on the sleepers, stresses and strains on the rail etc. In this work the vertical loads on the sleepers \( F_{l,r} \) and \( F_{l,l} \) are considered as inputs of the train detection algorithm (see Chapter. V); \( i \) refers to the \( i \)-th sleeper and \( r/l \) to the right or left slide respectively.

A. Measurement Layout

The train detection stations uses different measure layout characterized by various measure points (few if possible to reduce both the measure station dimensions and the economic costs) distributed along the railway track on the rail foot between two contiguous sleepers. On both the sides of the track measure points are present to reject the effect of spurious signals and of the load transfers produced by the lateral dynamics. In the present research activity, the layout of the adopted measurement station consists in three measure points on both rail side.

V. TRAIN DETECTION ALGORITHM

The train detection algorithm aims to determining different train parameters like the crossing time instants of vehicle and wheelset on the sleepers, its vehicle speed and axles number. The novelty of the proposed estimation method is that all these train quantities can be computed by means of only auto and cross-correlation operations. The track input used is the mean of maximum peak detection, followed by a time filtering through a cut-off threshold has been implemented to realize the axle counter function. All the post process operations are based on the cross-correlation and this represents a point of novelty of the proposed method. To test the algorithm performance, a series of simulation campaign with different vehicle weight, speed and noise level on the input signal has been made. The research has been carried out in cooperation with Ansaldo STS and ECM.

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4 illustrates the right and left vertical forces acting on the first sleeper: there are four peaks related to the four axles of the Manchester Wagon.

The operation of autocorrelation has been made on every obtained signals \( F_i^z \) and then the cross correlation has been made between all the possible pair of signals \( F_i^z \) and \( F_j^z \). In order to accurately reproduce the signal acquisition, a noise level has been added to the input signal (see Fig. 5).

Once applied a filtering stage to the input signal (with added noise), the correlation has been made, whose generic expression between two signals is:

\[
R_{ij}(m) = \frac{1}{N-m} \sum_{n=0}^{N-m-1} F_i^{z(n)} F_j^{z(n)}
\]  

(1)

digitized with \( N \) samples and \( m \) indicates the \( m \)-sample of the correlation signals. \( R_{ii}(m) \) indicates the auto correlation signal.

By means of correlation operations it is possible to evaluate the degree of true similarity between all pairs of signals to understand the characteristic of the examined signal. The second step is to focus the attention on the sample corresponding the maximum value of the cross correlation signal: starting from the difference between the sample corresponding to the maximum value of the autocorrelation of the signal \( F_i^z \) and the one corresponding to its cross correlation with the \( F_j^z \) signal, it is possible to compute the time delay between the \( F_i^z, F_j^z \) signals just multiplying this difference for the time integration step \( \Delta T \). Through this method, the time shift between all the pair of input signals can be easily determined. Once known the time delay, the vehicle speed can be compute just dividing the distance between the corresponding sleepers by the time shift previously found for the signals. An example with two sleepers spaced of \( d \) apart is reported in the following.

\[
m_i = \arg \max R_{ii}(F_i^z, F_i^z) \quad m_{ij} = \arg \max R_{ij}(F_i^z, F_j^z)
\]

(2)

\[
\Delta_{ij} = dt \cdot |m_{ij} - m_i| \quad V = \frac{d_{ij}}{\Delta T_{ij}}
\]

(3)

where \( m_i \) and \( m_{ij} \) are the sample number corresponding respectively to the maximum value of autocorrelation of \( i \)-th sleeper signal and the cross correlation between the \( i \)-th and the \( j \)-th one. \( dt \) is the sample time (equal to 0.001 s) and \( \Delta T_{ij} \) is the time shift between the \( i \)-th and the \( j \)-th force signal (corresponding to the two sleepers). \( V \) represents the vehicle speed, computed by dividing \( d_{ij} \) with the corresponding time delay \( \Delta T_{ij} \). Fig. 6 shows the case of time shift between the first and the tenth signals from the sleepers.

To compute the crossing time instants on sleepers it is sufficient to use the time signal shifting between sleepers, starting from the first to the last one.

\[
t_i = t_0 + \sum_{j=0}^{i-1} \Delta T_{j,j+1}
\]

(4)

The method used for the axle number detection is still based on the correlation theory: it has been decided to work
Fig. 6. Cross Correlation $R_{1,10}$ between the first sleeper signal $F_1$ and the tenth one $F_{10}$: the difference between the samples corresponding to their correlation maximum values multiplied by the time integrations step gives directly the time delay.

with the correlation signals rather than the direct signal coming from the force sensors because the correlation operation increases the signals of several orders of magnitude when there is a good degree of true similarity. In addition it has been observed that the peaks of true similarity, composing the correlation signal, are linked with the peaks of the original signal, representative of the passage of the axle on the sleeper. Fig. 7 illustrates the auto correlation signal when one, two or three of the axle peaks are present in the force signal instead of four.

The number of significant autocorrelation peaks decreases to seven if one axle is lost, decreases to two if two axles are lost and finally decreases to one if three axles loss happens. With this method, counting the autocorrelation peaks, it is possible to count even the signal force peak and hence the crossing train axles number. Once the auto correlation signal is obtained, it has been limited inside a sample window, whose size is determined in order to include only the significant samples (Fig. 8). An algorithm to determine the signal local peak is implemented (based on the signal $R_{1,i}$, on its derivative $R_{1,i}'$, see Fig. 9, and on suitable cut off threshold to localize the signal peaks from the noise peaks).

Fig. 7. Autocorrelation $R_{1,1}$ obtained with a different number of peaks present in $F_1$.

VI. PERFORMANCE OF THE TRAIN DETECTION ALGORITHM

This chapter describes the performance of the train detection algorithm for the estimation of the speed, crossing time instants on sleepers and train axles number starting from the knowledge, among all the possible measurements inputs of the vertical loads on the sleepers. The estimation algorithm has been tested through a simulation campaign, in which the attention is focused on the estimation behaviour in function of the vehicle speed, car body mass and input signal-to-noise ratio. For the testing of the estimation algorithm performances the reference measurement layout is the one represented in Fig. 3, composed by three force sensors located on the left and right side of three consecutive sleepers. In Tab. I the considered ranges of the previous quantities are reported together, where $N_v$, $N_M$, $N_{snr}$ represent respectively the number of simulated values of $V$, $t_i$ and signal to noise ratio SNR (the ratio between the power of the input signal and the one of noise input level).
TABLE I. VARIATION RANGES OF V, M AND SNR ADOPTED FOR THE SIMULATION CAMPAIGN

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Min.</th>
<th>Max.</th>
<th>N_sim</th>
</tr>
</thead>
<tbody>
<tr>
<td>Velocity (m\ s^{-1})</td>
<td>10</td>
<td>40</td>
<td>4</td>
</tr>
<tr>
<td>Car-body Mass (t)</td>
<td>10</td>
<td>50</td>
<td>5</td>
</tr>
<tr>
<td>Signal-to-noise ratio (dB)</td>
<td>5</td>
<td>15</td>
<td>3</td>
</tr>
</tbody>
</table>

VII. ESTIMATION OF THE CROSSING TIME INSTANTS ON THE SLEEPERS AND THE VEHICLE SPEED

In this section, the global performance of the algorithm in terms of vehicle speed and the crossing time instants on the sleepers are reported and studied by considering the relative error $e_{v}^{sim}(V,M,SNR)$ on 100 runs as follows (the maximum error value is considered):

$$e_{v}^{sim} = \frac{\hat{V}_{sim} - V}{V} \quad e_{t_{i}}^{sim} = \frac{\hat{t}_{sim}^{i} - t_{i}}{t_{i}}$$

where $V$ and $t_{i}$ represents the nominal value of the speed and crossing time instants respectively, and $\hat{V}_{sim}$, $\hat{t}_{sim}^{i}$ indicate their estimated ones.

The Fig. 10 shows a comparison between the time instants percentage errors, and their behaviour as a function of vehicle speed $V$ and car body mass $M$; each graph is related to a different value of the signal to noise ratio SNR of the input signal. In particular, for every SNR test case, the percentage errors on the first and third sleeper are reported (the first sleeper is assumed as reference and so coincident with a crossing time instant equal to zero).

Fig. 10. Percentage relative errors on the crossing time instants on the second (on the left) and third (on the right) sleeper as a function of nominal speed $V$ and car body mass $M$, for SNR=5 dB (top), 10 dB (middle) and 15 dB (bottom)

The maximum resulting error in the simulation campaigns is equal to 0.6 % and to 0.45 % for the second and third sleeper respectively, (related to a simulation performed considering the following values: $V$=30 meter/s, $M$=50 t and SNR=5 dB). The algorithm performance to estimate the crossing time instants on the sleepers is very important because the speed estimation uses the same time delays (between every pair of available sleepers) to perform the speed detection; therefore an estimation error on the time delays would deeply affect the same one on the speed. The following figure (Fig. 11) shows a comparison between the speed percentage errors and their behaviour as a function of vehicle speed $V$ and car body mass $M$; each graph is related to a different value of the signal to noise ratio SNR of the input signal.

Fig. 11. Percentage relative error on the speed as a function of nominal speed $V$ and car body mass $M$, for SNR=5 dB (top left), 10 dB (top right) and 15 dB (bottom)

According to the previous case, the maximum error occurs in the case of the simulation performed considering the following values: $V$=30 meter/s, $M$=50 t and SNR=5 dB. The obtained results highlight again even the good performance of the algorithm against different values of input signal to noise ratios, and consequently the capability of the algorithm to deal with measurements acquisition affected by a high noise level.

VIII. PERFORMANCE OF THE TRAIN DETECTION ALGORITHM AS AXLES COUNTING

The simulation campaign to test the algorithm capability as axles counting has been performed with variable vehicle parameters and input noise as indicated in Tab. II.

TABLE II. VARIATION RANGES OF V, M AND SNR ADOPTED FOR THE SIMULATION CAMPAIGN

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<td>40</td>
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</tr>
<tr>
<td>Car-body Mass (t)</td>
<td>10</td>
<td>50</td>
<td>5</td>
</tr>
<tr>
<td>Signal-to-noise ratio (dB)</td>
<td>8</td>
<td>12</td>
<td>5</td>
</tr>
</tbody>
</table>

The performance of the algorithm in estimating the train axles number has been evaluated considering the relative percentage error defined as follows:

$$e_{N}^{sim} = \frac{N_{sim}^{tot} - N_{tot}}{N_{tot}}$$

where $N_{tot}$ represents the number of crossing train vehicles and $N_{sim}^{tot}$ its estimation value. To test the axle counting performance, the results has been computed performing 100 runs of the algorithm, for each case of vehicle speed $V$ and car body mass $M$ (the maximum error is considered).

Results show the good performance of the estimation algorithm as axles counting, especially with an input SNR
TABLE III. MAXIMUM ERROR ON ESTIMATING AXLE COUNTER WITH VARIABLE SPEED V AND CAR BODY MASS M

<table>
<thead>
<tr>
<th>SNR dB</th>
<th>V= 10 m s⁻¹</th>
<th>V= 20 m s⁻¹</th>
<th>V= 30 m s⁻¹</th>
<th>V= 40 m s⁻¹</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>18%</td>
<td>16%</td>
<td>6%</td>
<td>12%</td>
</tr>
<tr>
<td>9</td>
<td>9%</td>
<td>3%</td>
<td>2%</td>
<td>4%</td>
</tr>
<tr>
<td>10</td>
<td>3%</td>
<td>1%</td>
<td>2%</td>
<td>3%</td>
</tr>
<tr>
<td>11</td>
<td>1%</td>
<td>0%</td>
<td>0%</td>
<td>2%</td>
</tr>
<tr>
<td>12</td>
<td>1%</td>
<td>0%</td>
<td>0%</td>
<td>1%</td>
</tr>
</tbody>
</table>

bigger than 11 dB, in which the percentage errors are below than 2%. The proposed method has showed the algorithm robustness to be apply for different vehicle speed V and car body mass M.

IX. CONCLUSION

In this paper the authors presented an innovative train detection algorithm with the aim of estimating the railway vehicle speed, its crossing time instants on the sleepers and finally its axles number. The studied vehicle is the Manchester Wagon composed by the car body, two bogies and four wheelsets. The algorithm is based on the measurement of the vertical forces on sleepers $F_{yi}$ and $F_{zi}$ performed through force sensitive elements placed over the sleepers in the section corresponding to the rail baseplate/pads. The developed algorithm can work both with real experimental or simulated data: the first comes from a physical model of the railway track, opportunely developed in order to test the algorithm performance when experimental data are not available. The novelty point of the proposed estimation algorithm is that it is only based on correlation operations to estimate all the different parameters of the railway vehicle. Another novelty of the paper consists in the general approach of the algorithm, that is applicable to different measurement layout and to different signals, measured on the track and used as input. A simulation campaign has been made in order to test the algorithm performance in estimating of the vehicle parameters as a function its speed V and car body mass M. In order to simulate different measurement operative condition, the vehicle parameters have been estimated with a signal to noise ratio starting from 5 dB to 15 dB: results highlight the good performance of the algorithm in estimating the crossing time instants on the sleeper and vehicle speed in all SNR range. The estimation algorithm has been also tested as axles counter highlighting good performances. Concerning the future developments, the aim is to optimize the estimation algorithm as train axles counter, combined with lower SNR values and with variable composition of the railway vehicle. From an experimental point of view, experimental tests are scheduled for the future by Ansaldo STS and ECM Spa. The experimental data will concern wagons travelling at high speeds and wagons characterised by different geometries as the axles number.

REFERENCES