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Pantograph-Catenary Contact Force Estimation from Linear Camera Images

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Abstract

Traditional contact force measurement methods are expensive and impractical for regular train operation. This study proposes estimating pantograph-catenary contact force using linear camera images of collector head vertical movement and artificial intelligence tools such as artificial neural networks. The whole procedure is based on experimental measurements performed on a pantograph test bench. From the linear camera images taken of the contact strip, two methods were proposed to obtain the collector head acceleration. Then, in the second step, the contact force is estimated. The results obtained show an overall excellent accuracy when compared to the measured magnitudes on the test bench with a root mean square error of 4.8 N. To obtain this accurate contact force prediction is preferable to take longer acceleration intervals before the prediction time step.

Keywords: catenary, pantograph, artificial neural networks, condition monitoring, linear camera, contact force.

1 Introduction

Failures in the energy supply system of electric trains can cause delays in circulation or even endanger the safety of passengers. Therefore, it would be advisable to continuously monitor the catenary to enable proper maintenance operation planning and increase system reliability.

Regarding catenary monitoring, in recent years, the number of publications has significantly increased [1], focusing on various aspects such as detecting the contact point, wear of the contact wire, arcing, or the contact force between the pantograph and the catenary, which is the focus of this study. Typically, the standardized method for measuring the contact force [2] requires an instrumented pantograph mounted on a dedicated vehicle. The measurement procedure is relatively costly and is not suitable for its use on a regularly operated train. As an alternative, estimating the contact force from indirect measurements on the pantograph is proposed. For example, in [3], the strain of the contact strips is used to obtain the contact force, or in [4], this force is derived from acceleration measurements of the collector head.

In this work, we propose estimating the pantograph-catenary contact force between the pantograph and the catenary using linear camera images of the vertical movement of the collector head and artificial neural networks (ANN). For the development and validation of the proposed methodology, measurements obtained from a pantograph test bench have been utilized.

The proposed approach is presented in Section 2 while the main results obtained are discussed in Section 3. Section 4 ends this work with some conclusions.

2 Methods

The methodology proposed to estimate the contact force applied on the pantograph from the images of the pantograph head is summarised in Figure 1. First, from the power spectral density (PSD) of the contact wire height error, a set of 10 catenary models is built and simulated with the software PACDIN [5], giving as a result the contact wire vertical displacement. This displacement is sent to the linear motor in the test bench, which imposes it on the pantograph contact strips. On each test, the contact force on the pantograph head is measured with two load cells, and a linear camera provides a grayscale image of a light source installed on the contact strip.

A first artificial neural network is trained taking as input the linear camera image at a given time step and predicting the vertical displacement of the pantograph collector head. This predicted displacement is low-pass filtered to 20 Hz, and the acceleration is computed with a central finite differences scheme. Then, following a similar procedure as that proposed in [6], a second ANN is trained from the acceleration signal in a short period to predict de contact force. The details of each step are presented in the following subsections.

2.1 Initial data

The data set used in this work is composed of 10 catenary models that include two overlap sections each. As described in [6], the PSD of the contact wire height error is obtained from measurements of installed catenary sections. By setting a random phase, 10 sets of contact wire height errors were obtained. These were set as input of the PACDIN software which first, computes the shape-finding problem to obtain an FE model of the catenary that fulfils these contact wire height specifications at the dropper connection points. Then, the pantograph-catenary dynamic interaction simulation is performed [7] with a lumped-mass pantograph model and a penalty approach to model the contact between the pantograph and the contact wire. The simulations are run considering random train speeds from 250 to 300 km/h. As a result, we have the vertical displacement of the contact point for the 10 simulations. Note that each initial sample has a different size since the length of the catenary section simulated is the same, but the train speed differs from one simulation to the other.

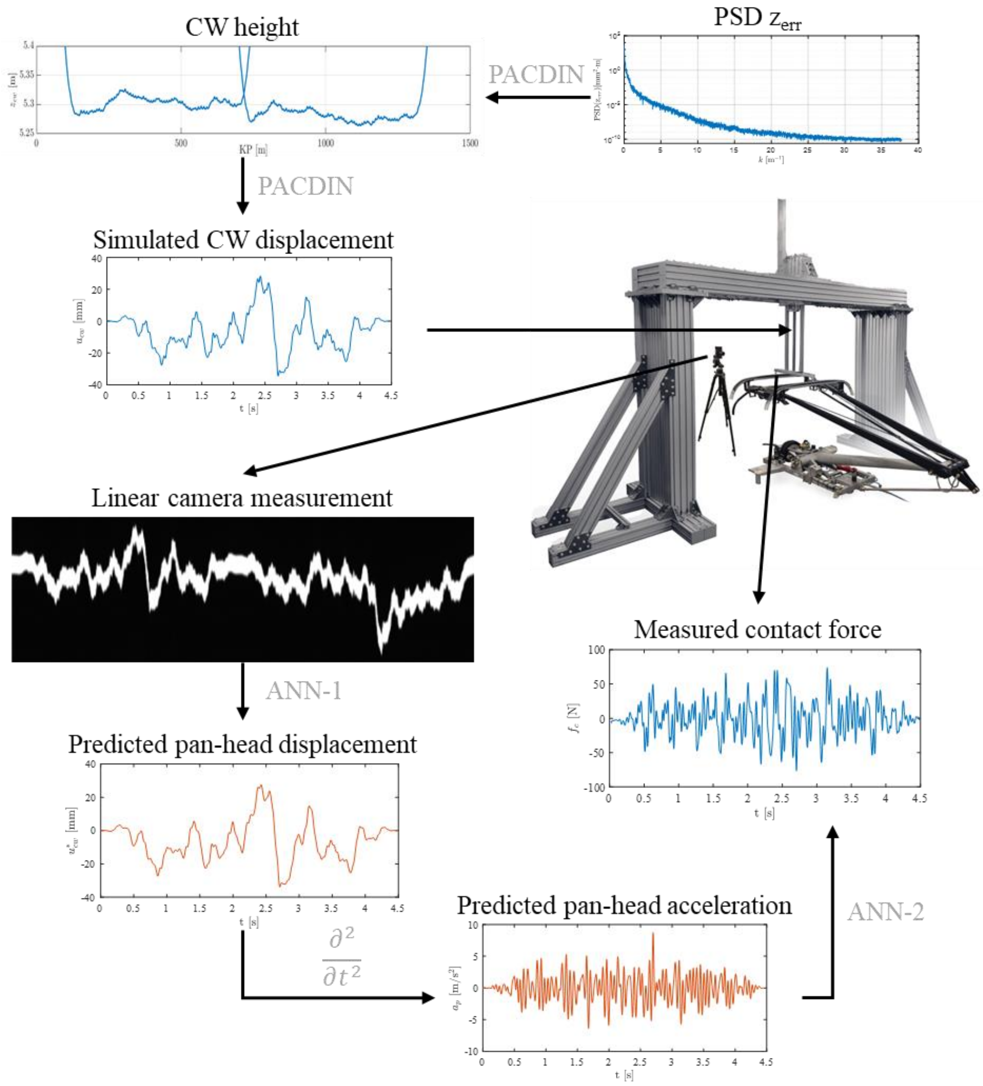

Figure 1: Flow diagram of the method proposed to estimate the contact force from linear camera images.

2.2 Experimental tests

The vertical contact wire displacement, u_{cw}, obtained from simulation, is imposed to be followed by the linear motor on the test bench, which in turn, moves vertically the pantograph head as shown in Figure 2.

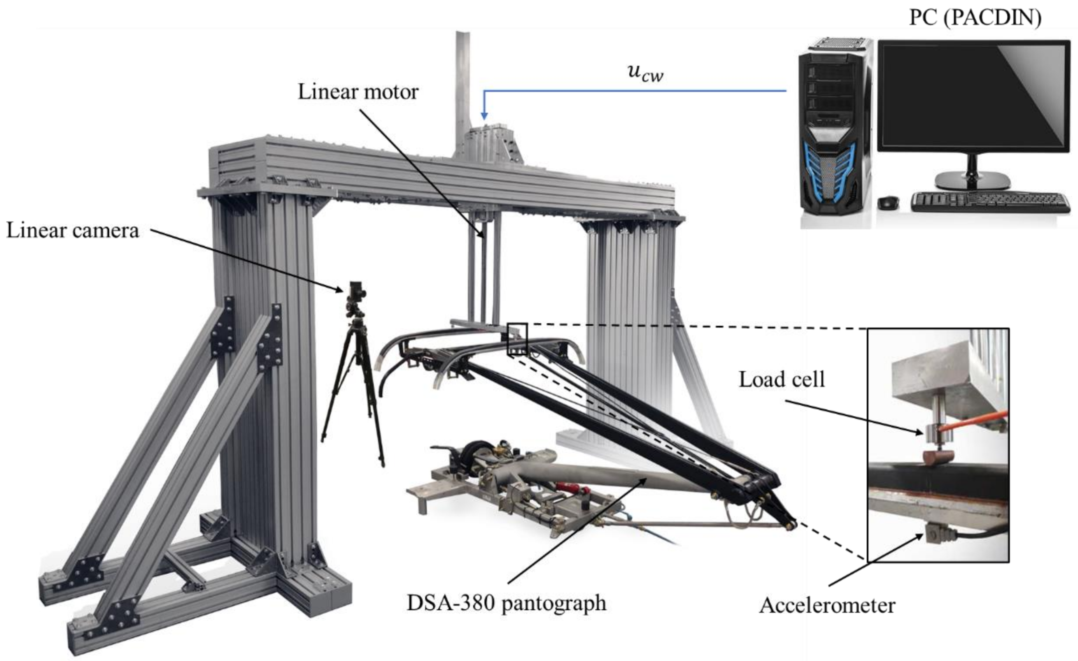

Figure 2: Test bench with its main components [8].

At each test, four signals are measured synchronously at a rate of 500 Hz. With two load cells, the force applied at each contact strip is collected, being the total force the sum of these two signals. The vertical acceleration of each contact strip is also measured. In this case, the vertical acceleration of the pantograph head is the mean value of these two accelerations. The linear motor driver also provides the displacement of the motor, which in fact, is the vertical displacement of the pantograph head. Additionally, the linear camera Aviiva from Teledynedalsa (Waterloo, ON, Canada), with a resolution of 8192 pixels, is installed. The camera is framed to an LED light source, placed on the lateral side of one contact strip, which is used as a marker that facilitates image processing. Figure 3 shows an example of the image obtained from a given test, which was trimmed to 3100 pixels.

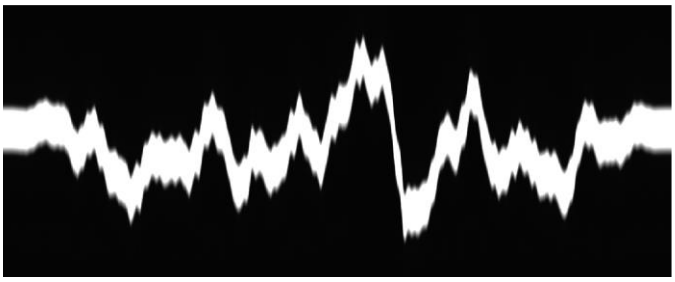

Figure 3: Image captured by the linear camera on a given test.

2.3 Prediction of acceleration from linear images

The next step is to predict the pantograph head acceleration from the images captured by the linear camera as shown in Figure 3. To this end, we propose two strategies: i) the use of an artificial neural network, and ii) selecting the midpoint of the saturated region of the image.

The ANN proposed, takes as input the vector containing the grayscale values of the image at a given time step and returns the pantograph head displacement at this time step. The grayscale value is first scaled to range from 0 to 1 and at each time step it is a vector of 3100 pixels in length. The hyperparameters defining the ANN are selected heuristically to provide accurate results. Specifically, we end up with a regression neural network containing two layers of 500 and 250 neurons each and ReLU activation functions. 8 samples are used to train the ANN while the other 2 are left for validation purposes.

The second strategy consists of detecting the pixels in which clipping occurs (the scaled grayscale value is 1) and selecting the intermediate pixel of this region for every time step. This procedure is exemplified in Figure 4 for a given time step, in which the shaded grey is the clipped region, and the red marker is the final selected pixel. Finally, the result of this procedure is converted to length units scaling by a calibrating factor of millimetres per pixel.

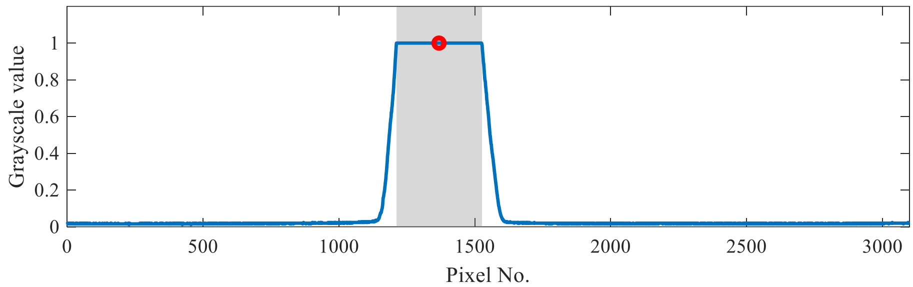

Figure 4: Scaled grayscale values for a given time step. Pixel selection at the middle of the clipped region.

Once the displacement of the pantograph head is known by one of the two methods proposed, it is low-pass filtered to 20 Hz and derived twice over time by using a central differences scheme.

2.4 Prediction of contact force from acceleration

Another ANN carries out this last step. In this case, it takes as input a given prediction interval of the acceleration computed in previous stages of the proposed procedure and returns the contact force (the force applied to the pantograph) of a single time step. Figure 5 shows the described input for the time 4.6 s. The prediction interval $[t - N_t^{ant}, t + N_t^{pos}]$, can be adjusted to improve the prediction accuracy as discussed in Section 3.2.

The layout of this ANN is the same as that of the ANN used to predict displacement from the linear camera image. Also, 8 acceleration samples are used to train the network and the other 2 are used to validate its predictions. It is important to remark that this method is not able to predict the mean value of the contact force. However, this is not a big limitation since the mean value does not affect the standard deviation which is used as a parameter to quantify the current collection quality and it is eventually the final goal of the proposed method.

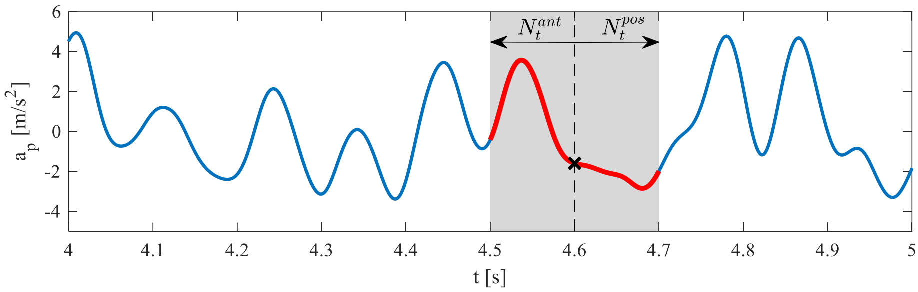

Figure 5: Example of the input of the ANN (red curve) to predict the contact force at the time step highlighted with a cross marker.

3 Results

The results shown in the subsequent sections are aimed at assessing the accuracy of the two prediction stages of the proposed method to estimate the contact force from linear camera images of the contact strip. First, the prediction of the vertical acceleration from the image is assessed and then the prediction of the contact force from the acceleration. For this, we use the two samples not involved into the training process.

3.1 Assessment of the predicted acceleration

First, the accuracy of the two methods proposed to obtain the pantograph head vertical displacement from the linear camera images is observed in Figure 6. Both strategies provide very good results when compared with the measured displacement provided by the motor controller. However, from a closer view of Figure 6, the prediction made by the ANN fits better the measured displacement, maybe due to the middle-pixel approach if affected by the distortion of the image when the LED light moves away from the central position.

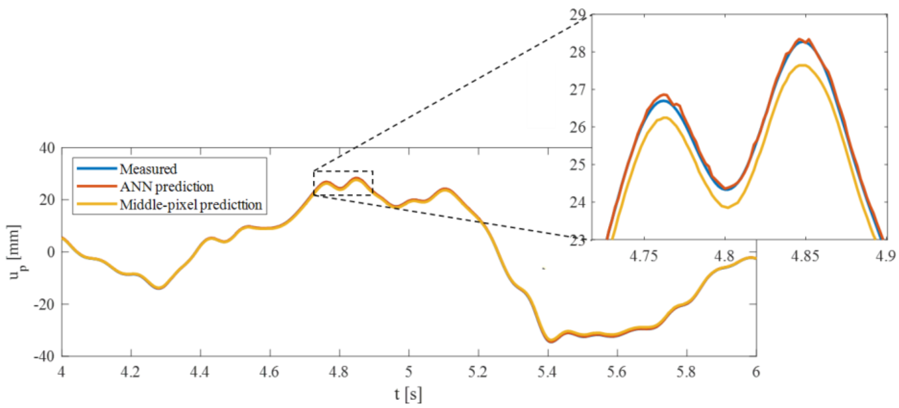

Figure 6: Comparison of the obtained displacement from both the ANN and the middle-pixel methods with the measured displacement.

Then, this displacement is low-pass filtered and derived twice with respect to time to obtain the vertical acceleration of the pantograph head. Figure 7 shows a comparison of the obtained acceleration from both displacement prediction methods with the measured acceleration in the test bench. Again, the two methods lead to very good acceleration prediction, being the ANN-based a bit more accurate.

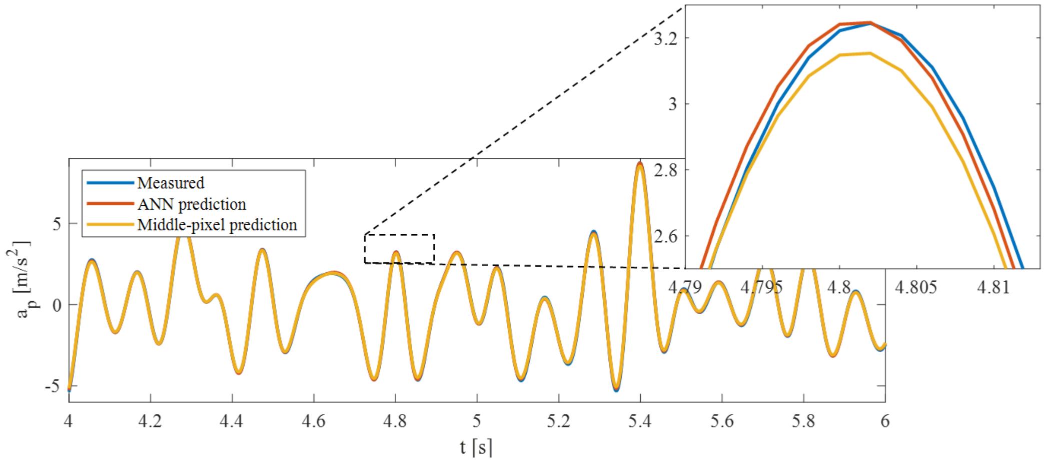

Figure 7: Comparison of the obtained acceleration from both the ANN and the middle-pixel methods with the measured acceleration.

To quantify the accuracy of both methods in obtaining displacement and acceleration from the linear camera image, we use the relative root mean square error (RRMSE). For a given magnitude y with N time steps, it is defined as:

$$E = \frac{1}{N|y|_{max}} \sqrt{\sum_{t=1}^{t=N} |y_t^* - y_t|^2} \tag{1}$$

being y_t the measured magnitude at time step t, $|y|_{max}$ its maximum absolute value, and y_t^* the predicted value at time step t. In Table 1, the RRMSE for displacement and acceleration prediction from the two methods proposed is provided. The ANN prediction is more accurate mainly for the displacement prediction. After filtering and derivation, both method produces a similarly accurate acceleration prediction.

	Displacement [-]	Acceleration [-]
ANN prediction	0.055	$1.03 \cdot 10^{-2}$
Middle-pixel prediction	0.173	$1.26 \cdot 10^{-2}$

Table 1: RRMSE of the displacement and acceleration prediction from a linear camera image.

3.2. Assessment of the predicted contact force

The strategy described in Section 2.4 is validated in this section. Table 2 shows the RMSE (note that it is an absolute error measured in N) of the predicted contact force for different combinations of N_t^{ant} and N_t^{pos}, i.e. for different length of the input acceleration signal in the ANN.

	N_t^{pos}		
N_t^{ant}	50	100	200
50	8.86	8.06	7.09
100	7.53	6.33	6.48
200	5.93	5.36	5.22
300	4.80	4.77	4.91

Table 2: RMSE [N] of the predicted contact force.

These results show that for a more accurate prediction is more important to consider acceleration values measured before the prediction time step than the acceleration after this point, whose amount barely affects the prediction accuracy. In fact, for a large enough acceleration time interval before the prediction time step ($N_t^{ant} = 300$), it is not necessary to include subsequent acceleration values.

Figure 8 shows a comparison between the predicted and measured contact force for one of the two validation samples, taking the two acceleration prediction intervals shaded in green in Table 2. It can be noticed that with $N_t^{ant} = 300$ the predicted force, in general, is more similar to the measured force. However, the other example shown ($N_t^{ant} = 50, N_t^{pos} = 200$) also exhibits a good similarity to the measured magnitude.

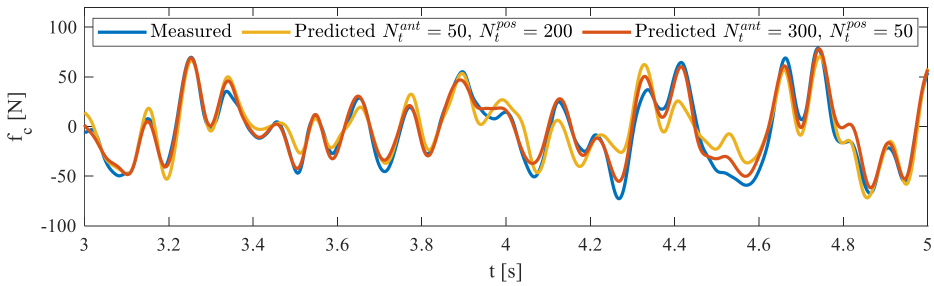

Figure 8: Comparison of the predicted acceleration from two different prediction intervals.

4 Conclusions and contributions

This paper proposes a method to estimate de pantograph-catenary contact force from images that capture the movement of a contact strip. For this, the first step consists of predicting the vertical collector head acceleration from linear camera images, in which the proposed ANN-based approach generally shows superior performance compared to the middle-pixel method. This suggests that the ANN approach is more robust and less susceptible to image distortion effects. The second step of the method proposed consists of predicting the contact force from the acceleration of the collector head. The results emphasize the significance of considering acceleration values measured before the prediction time step as input of the ANN for accurate contact force prediction. Despite variations in the length of input acceleration signal intervals, the

ANN predictions remain robust, yielding satisfactory similarity to measured contact forces. This suggests that the proposed methodology is versatile and capable of producing reliable predictions across different scenarios.

Estimating pantograph-catenary contact force using images of vertical collector head movement and ANN shows promise as a viable method for continuous monitoring and maintenance planning in electric train systems. The methodology developed and validated in this study demonstrates the potential for enhancing system reliability and safety while reducing costs associated with traditional contact force measurement methods.

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