Proceedings of The 2008 International Conference on Artificial Intelligence

Proceedings of The 2008 International Conference on Machine Learning; Models, Technologies and Applications

ICAIS

Volume II

Editors

Hamid R. Arabnia Youngsong Mun

Associate Editors

David de la Fuente, Elena Kozerenko Peter M. LaMonica, Guo-Zheng Li Raymond A. Liuzzi, Jose A. Olivas Gene Simmons, Ashu M. G. Solo



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Proceedings of The 2008 International Conference on Artificial Intelligence

&

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This set of volumes contain papers presented at The 2008 International Conference on Artificial Intelligence (ICAl'08) and The 2008 International Conference on Machine Learning; Models, Technologies and Applications (MLMTA'08). Their inclusion in this publication does not necessarily constitute endorsements by editors or by the publisher.

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Foreword

It gives us great pleasure to introduce this collection of papers to be presented at the 2008 International Conference on Artificial Intelligence (ICAI'08) and the 2008 International Conference on Machine Learning; Models, Technologies and Applications (MLMTA'08), July 14 through 17, 2008, at Monte Carlo Resort, Las Vegas, USA.

The Academic Co-Sponsors of this year's conferences include:

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Organizers and Other Co-Sponsors at-large include: A number of university faculty members and their staff (names appear on the cover of the proceedings); World Academy of Science (www.world-academy-of-science.org/); Computer Science Research, Education, and Applications Press; High Performance Computing for Nanotechnology (HPCNano); International Technology Institute (ITI); GridToday; HPCwire; and Hodges' Health (H2CM), United Kingdom. In addition to the above, several publishers of computer science and computer engineering books and journals, chapters and/or task forces of computer science associations/organizations from 12 countries, and developers of high-performance machines and systems provided significant help in organizing the conferences.

The ICAI and MLMTA program committees would like to thank all those who submitted papers for consideration. About 65% of the submissions were from outside the United States. Each submission was evaluated by two referees (except for papers that were submitted directly to chairs of sessions who were responsible for the evaluation of these papers.) The overall paper acceptance rate for regular papers was 27%; 11% of the remaining papers were accepted as short papers.

We are very grateful to the many colleagues who helped in organizing both conferences (ICAI'08 and MLMTA'08). In particular, we would like to thank the members of the ICAI'08 and

MLMTA'08 Program Committees who we hope will offer their help again in organizing the next year's conferences. The ICAI'08 Program Committee members were:

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We present the proceedings of ICAI'08 and MLMTA'08.

Hamid R. Arabnia and Youngsong Mun General Co-Chairs and Coordinators, ICAI'08/MLMTA'08

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SESSION: INTELLIGENT LINGUISTIC TECHNOLOGIES - ILINTEC'08

Monitoring Vertical Acceleration of Railway Wagon using Machine Learning Technique

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Abstract—Wireless communications and modern machine learning techniques have jointly been applied in the recent development of vehicle health monitoring (VHM) systems. The performance of rail vehicles running on railway tracks is governed by the dynamic behaviors of railway bogies especially in the cases of lateral instability and track irregularities. In this study we have proposed a system to monitor the vertical displacements of railway wagons attached to a moving locomotive. The system uses a classical linear regression machine learning technique with real wagon body acceleration data to predict vertical displacements of vehicle body motion. The system is then able to generate precautionary signals and system status which can be used by the locomotive driver for necessary actions. This VHM system provides forward-looking decisions on track maintenance that can reduce maintenance costs and inspection requirements of railway systems.

Keywords - Vehicle health monitoring; vertical acceleration; machine learning; bogic dynamics

I. INTRODUCTION

Advances in information and communication technology have enabled the adoption of machine learning techniques in all sectors to solve real world problems in business, engineering and sciences. In order to ensure reliable, safe and secure operation of railway systems it is essential to adopt intelligent monitoring systems for railway wagons. A system designed for railways to limit the risk of injury to persons or damage to property and ensure safe and reliable operations is called a "rail safety management system". Safety of a system can be considered in the context of the more general concept of dependability and a dependable system is one which is reliable, available, maintainable and secure. Typical dynamic behaviors of railway wagons are responsible for the safe and reliable operation of freight railways. The dynamic performance is determined by the characteristics of the wagon and the irregularities in the track. Railway track irregularities need to be kept within safe operating margins by undertaking appropriate maintenance programs [1],[2],[3].

Railway wagons are intended to guide the load along the track safely with minimal damage to the track and the load. Railway tracks are designed to interface with railway vehicles to support the load while providing a permanent path of travel. It is identified that the performance of rail vehicles running on a track is limited by 1) the lateral instability inherent to the design of the steering of a railway wagon 2) the response of

the railway wagon to individual or combined irregularities. Generally, specialized track geometry measurement vehicles are used to determine track conditions. However, this alone is not a good predictor of railway vehicle response [3],[4].

Predicting vehicle characteristics online from track measurement data has been addressed by various research organizations [5],[6],[7],[8],[9],[10],[11]. Esveld outlines a multiple input single output transfer function based system used in the Netherlands named Vehicle Response Analysis (VRA) [5]. Joseph et al. [6]introduced the ZTLMM (ZETA-TECH Lumped Mass Model) system for predicting the response of rail vehicles to measure track geometry in real time. Car body vertical displacement (bounce), car body roll and pitch angles, vertical wheel/rail forces and vertical car body accelerations are predicted with this system. These characteristics are used to assess the safe behavior of the vehicle. The ZTLMM system matches with the NUCRAS (New and Untried Car Analytic Regime Simulation) model.

Freight wagon instrumentation studies have shown that severe dynamic forces occur when irregular wavelengths and train speeds combine to excite a resonant mode in the vehicle [7],[8]. A remote monitoring system was developed by Amtrak [9] for daily measurements of car body and truck accelerations. This system measures car body and truck motions, detects various acceleration events, and tags them with GPS time and location information. This information is then delivered to central processing stations via a wireless communication system. In order to ensure reliability and availability there are multiple levels of protection and redundancy in these systems [9]. Sato et al. [10] introduced the Track Information Processing System (TRIPS) to identify track irregularities and vehicle responses on the test train running at speeds in excess of 300 km/h. All the signals are picked up with non-contact sensors and input to a computer. With this system all the characteristics of irregularities in the test section can be seen at a glance and the defects can be read easily through the computer system.

Central Queensland University (CQU), in association with the Centre for Railway Engineering (CRE) [11], has been investigating a Health Card device for railways. This Health Card system is an autonomous device used for the analysis of car body motion signals that can detect track conditions and monitor derailment conditions. The Health card is capable of resolving car body motions into six degrees of freedom. To do this the Health Card uses accelerometers and angular rate sensors with a coordinate transform. Two prototypes have been developed based on wired and wireless solutions. The Health Card system uses fast Fourier transforms to efficiently convert the signal into a time-frequency spectrograph so that events can be detected according to their short-term spectral content. From spectral analysis, it has been found that small residual responses exist in the pitch and yaw degrees of freedom and the wagon was not laterally constrained [4],[11].

The Transportation Technology Center, Inc. (TTCI), USA conducted a performance-based track geometry study that involved extensive field tests as well as modeling efforts. Vehicle/track interaction tests have included measurements of both track geometry and responses of several typical freight vehicles under typical revenue service conditions. The modeling efforts have led to the successful development of neural networks relating complex track geometry inputs to vehicle response [12]. Nefti et al. [13] used artificial neural networks (ANNs) architecture to predict railway systems malfunctioning due to track irregularities. Different neural network structures are created to find out the best structure for predicting railway safety. Cen et al. [14] investigated a machine learning approach to automate the identification process of railroad wheels using collected data from wheel inspection. A Decision tree and SVM based classification scheme is used to analyze the railroad wheel inspection data. The experimental results indicate that the proposed approach is very efficient, producing a classifier ensemble that has high sensitivity and specificity during classification [14],[15].

Linear regression analysis was used to predict dynamic characteristics of worn rail pads. The curve fitting approach showed the maximum correlation of dynamic stiffness and damping of worn rail pads under preloads while achieving less than 4 percent error for all pads. Linear regression analysis was used to predict the deterioration rate with age of dynamic stiffness and damping coefficients. Results shows that the per-MGT rate of rail pad degradation in terms of dynamic stiffness is about 2.18 MN/m and the rate for the damping is approximately 19.63Ns/m [16].

To monitor lateral instability and track irregularities in this study, train wagon body acceleration signals, i.e., six degrees of freedom (DOF) or six modes of vehicle body motion: roll, pitch, yaw, lateral, vertical and longitudinal modes were investigated using machine learning algorithms. In this paper we investigated vertical or bounce and pitch modes of a railway wagon and predicted vertical acceleration at the rear location of the wagon body. The linear regression algorithm is used to predict vehicle vertical acceleration motion and generate alarm signals if it is beyond preset safety limits and informs the driver for necessary action. This paper is organized as follows. Section III discusses the method to measure vertical acceleration. Section III presents the experimental design of applying linear regression analysis on the measured data. Experimental results are described in Section IV. Section V.

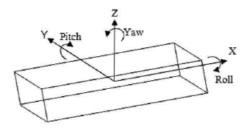


Fig. 1. Six degrees of freedom of wagon movement

concludes the article with future directions.

II. MEASUREMENTS OF VERTICAL ACCELERATION

A three-dimensional coordinate system is normally used to narrate dynamic behaviors of railway wagon having six DOF. Linear motion along the X, Y and Z axes are termed as longitudinal, lateral, and vertical translations respectively. Rotary motions about the X, Y and Z axes are termed as roll, pitch and yaw respectively as illustrated in Fig.1. The vertical displacements of wagon, i.e., the deflection in between up and down is called bounce mode. The rotation around the side-to-side axis of train wagon or tilting up and down is called pitch mode. A set of four prototypes "Health Cards" [11] has been developed by a team at Central Queensland University. Each prototype "Health Cards" incorporates a 27 MHz microcontroller with 256kB of onboard RAM, four dual-axis accelerometers, a GPS receiver, two low power radios, lithium ion batteries and a solar panel.

Steven et al. [4],[11] placed dual-axis accelerometers to each corner of the body and each side frame. Sensor locations and naming are given in Fig. 2. The aim of the sensing arrangement was to capture roll, pitch, yaw, vertical and

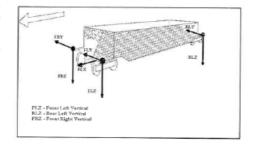


Fig. 2. Accelerometer locations and Axis naming convention [4]

lateral accelerations of the wagon body. ADXL202/10 dual-axis acceleration sensor measured 16 channel acceleration data in g units. Data was collected from a ballast wagon which was a conventional three piece bogie spaced $l_b=10.97\mathrm{m}$ apart. The accelerometers were spaced $l=14.4\mathrm{m}$ apart. The test run was a normal ballast lying operation, starting with a full load of ballast, traveling to the maintenance site, dropping the ballast on the track, and returning empty via the same route. A PC based data acquisition system was used to store data [4],[17].

Data used in this study is from the data collected by the Centre for Railway Engineering (CRE), CQU [11] of the car body motion signals to detect track conditions and provide derailment monitoring. For this experiment to calculate bounce and pitch modes of wagon body we have used 3 channels of data out of the 16 collected, i.e., 'front left vertical, FLZ', 'rent left vertical, RLZ', 'front right vertical, FRZ'. AFLZ, ARLZ and AFRZ are respectively the averages of FLZ, RLZ, and FRZ.

To calculate vertical or bounce mode behavior of railway wagons we have used the equation below as stated in [4]:

$$VERT = [FRZ - AFRZ + RLZ - ARLZ]/2 \quad (1)$$

We have considered l_b , the distance between bogies and l, the distance between transducer to calculate pitch mode acceleration. Calculated pitch mode acceleration is:

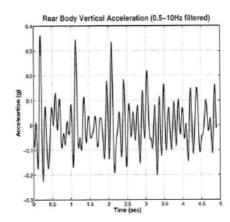
$$PITCHACC = \{(FLZ - AFLZ - RLZ + ARLZ)/l\} * l_b/2$$
(2)

Rear body vertical acceleration has been measured finally using:

$$RVertACC = VERT - PITCHACC$$
 (3)

The existing ride monitoring systems and associated standards apply peak to peak and RMS measures to create an exception. The Australian Railway Standards specify lateral and vertical accelerations for new and modified rolling stock. According to the Australian ride performance standards the peak to peak body vertical acceleration limit is 0.80g and average peak to peak body vertical acceleration is 0.50g. All acceleration signals in the Australian railway standards are to be filtered to below 10Hz [18],[19].

For this study according to existing ride monitoring systems we have used the Australian Standard RMS limits to monitor the signal condition. A graphical representation of measured rear body vertical acceleration using the stated formula and available data is illustrated in Fig. 3 and Fig. 4. From several datasets collected in the study [4], in this paper we have highlighted two data sets as examples in which major vertical displacement occurs. Here we have used two instances of data sets, each of 5 seconds duration. Both of the data samples were collected in loaded wagon conditions and filtered to 0.5-10Hz. The filtering has been done in the frequency domain by using the Fast Fourier Transform (FFT) with Hanning windows as used in [4]. In Fig. 3 the top figure represented rear body vertical acceleration behavior of raiway wagons. The



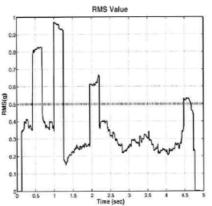
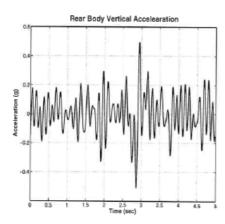


Fig. 3. Top fig.: Rear body vertical acceleration characteristics (0.5 -10 Hz filtered), Bottom fig.: Measured RMS value from filtered signal for data set 1. Major vertical deflection observed.

signal has been band-pass filtered to remove the low frequency content below 0.5 Hz and the high frequency content above 10 Hz. Bottom figure represented measured RMS value from the filtered signal. The RMS value has calculated over a 2 second period in steps of one sample. Typical vertical displacement observed for both the data sets and the RMS output is beyond the safety limit. However, for the data set 2 there is lower vertical deflection deviation than the data set 1. Therefore, it is an urgent need to take special attention and create warning signal for these instances as RMS value is above the safety limit.



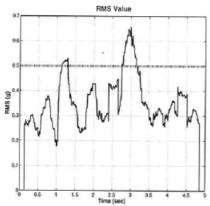


Fig. 4. Top fig.: Rear body vertical acceleration behavior (0.5-10 Hz filtered), Bottom fig.: Measured RMS value from filtered signal for data set 2.

III. MACHINE LEARNING TECHNIQUES TO PREDICT VERTICAL ACCELERATION

To monitor typical dynamic behavior of railway wagons due to track irregularities and lateral instability in this study we have investigated vertical acceleration phenomenon. The linear regression algorithm has been used to predict a ballast wagon's vertical displacement. At the beginning of the experiment raw data was stored for pre-processing as there is a possibility to include noisy and unwanted data in the datasets.

After pre-processing of the data a suitable learning algorithm was identified for the experiments. We have selected linear regression analysis for these experiments. From the literature survey it has been observed that linear regression analysis can predict linear time series data more efficiently than the simple linear regression and support vector machine (SVM) regression analysis in terms of error rate and running cost [20], [21].

Regression analysis [21],[22],[23] is a statistical forecasting model that addresses and evaluates the relationship between a given variable (dependent) and one or more independent variables. The major goal in regression analysis is to create a mathematical model that can be used to predict the values of a dependent variable based upon the values of an independent variable. It is a regression method that models the relationship between a dependent variable Y, independent variables X_i , where i = I...p, and a random number ϵ . The model can be written as:

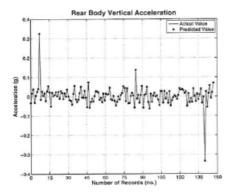
$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + + \beta_p X_p + \epsilon$$
 (4)

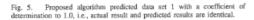
This method is called "linear" because the relationship of the dependent variable Y to the independent variables X is assumed to be a linear function of the parameters. However, if the model is: $Y=\alpha+\beta x+\gamma x^2+\epsilon$, in which Y is a linear function of parameters $(\alpha,\beta,$ and $\gamma)$, it may not be a linear function of x.

The regression model is used to predict the value of Y from the known value of X and find the line that best predicts Y from X. Linear regression does this by finding the line that minimizes the sum of the squares of the vertical distances of the points from the line. It assumes all the data are linear, and finds the slope and intercept that makes a straight line best fit for training data. The goodness of fit and the statistical significance of the estimated parameters are a matrix of regression analysis. Commonly used checks of goodness of fit include r-squared. The coefficient of determination r^2 is the proportion of variability in a data set and the value of r^2 is a fraction between 0.0 and 1.0. If r^2 equals 1.0, all points lie exactly on a straight line with no scatter, this is the best-fit situation.

After necessary pre-processing we have formatted the data so that it was ready to use in the linear regression algorithm for further analysis. For initial data pre-processing, and formatting we have used MATLAB [24] and WEKA [25] learning tools. WEKA includes a comprehensive set of data pre-processing tools, learning algorithms and evaluation methods, graphical user interfaces and environment for comparing learning algorithms [26]. By adopting the linear regression method we have developed an algorithm to predict rear body vertical acceleration characteristics with the help of WEKA learning tools. This proposed algorithm is very simple; initially it prepares input using the above formulation (equs. 1-3) and then feeds the input into the linear regression model.

First, we have used the proposed model with a percentage spilt test and training data sets. This test set has used to evaluate how well it predicts a certain percentage of the data which is held out for testing. The amount of data held out depends on the value entered in the percentage field. We have used percentage split to 70 percent, i.e., 70 percent of the data





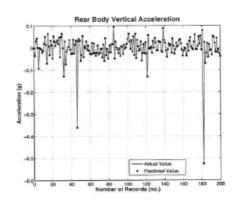


Fig. 6. For data set 2 we observed an identical graph, i.e, actual data and predicted data are identical.

for training and the remaining 30 percent data for testing. We have predicted rear body vertical displacement characteristics with the measured rear body vertical acceleration data. From experiments it has been shown that our algorithm predicted vertical acceleration characteristics with a negligible error for rear side of the train wagons.

Finally, with the predicted rear vertical acceleration data, our algorithm has been devised to generate precautionary signals if the data is beyond the safety limit. Initially the signal has been filtered by FFT and the measured RMS value. Based on the measured RMS signal, a precautionary signal has been generated to train drivers. For our experiment we have used the Australian ride performance standard which is the 0.50g average peak to peak for body vertical acceleration. Signals sent to the driver through wireless communications systems for informed forward-looking decisions and initiation of suitable actions prevent disastrous accidents from happening.

IV. RESULTS AND ANALYSIS

Proposed algorithms with percentage split test options were used to predict the vertical displacement behavior of a railway ballast wagon. We have used two sets of data in different instances, i.e., different times and locations. The duration of each data set is around 5 seconds. For the first data sets, we have developed a new algorithm by adopting the linear regression method to predict vertical acceleration scenarios in the rear side of the train wagons. With percentage split to 70 percent proposed algorithm achieved maximum accuracy to predict rear vertical acceleration data and coefficient of determination, r^2 is to 1.0. We did the same experiment using a different percentage split. Almost the same result has been observed for each percentage split, i.e., results didn't vary with the variation of percentage splits. We have also analyzed this model with fewer data records, i.e., around 1200 records. The

result was different in the case of fewer records where we have achieved coefficient of determination to 0.996. It has seen that the proposed algorithm predicted more successfully in the case of large data records. We have run the same model for a second data set and observed almost identical results.

We have tested our algorithm to verify the warning signal for train drivers. The results show that the model could produce a warning signal if the predicted data is above the prefixed threshold value.

V. CONCLUSION

Intelligent machine learning techniques play a key role in developing monitoring systems for both freight and passenger railway systems to ensure safety and security, both inside the wagon and on the rail track. To investigate track irregularities and lateral instability in this paper we have highlighted bounce and pitch mode behaviors of railway wagons. A model has been developed using a linear regression algorithm to predict vertical acceleration in the rear side of the train wagon. The experimental results show that the approach is very effective and predicted rear vertical movement characteristics with a negligible error and the coefficient of determination is almost 1.0. This useful tool can be used to monitor railway systems with integrity and reliability which reduces costs due to data collection and calculation. It also reduces power consumption of the system and increases the sensor's lifetime. This is the first time that modern machine learning techniques have been used in this context but they still require verification in different areas. Therefore, it deserves further investigation that will focus on these specific areas:

- · investigate lateral acceleration of rail wagons
- predict front end rail wagon behavior from rear wagon collected data
- · select most suitable algorithm using trial-and-error basis

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