Rail monitoring from the dynamic response of a passenger train

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ABSTRACT: In this case study, we monitor Pittsburgh's light rail-network from sensors placed on passenger trains, as a more economical monitoring approach than either visual inspection or inspection with dedicated track vehicles. Over time, we learn how the trains respond to each section of track, then use a data-driven approach to detect changes to the track condition relative to its historical baseline. We instrumented the first train in Fall 2012, and the second train in Summer 2015. We have been continuously collecting data on the trains' position using GPS and their dynamic response using accelerometers; in addition, we have the track maintenance logs from the light-rail operator. As a validation of our system, we have been able to detect changes in the tracks, which correspond to known maintenance activity.

Test Structure and Measured Data

Our effective "test structure" is Pittsburgh's 30km light-rail track network. This network has been pieced together over more than a century; the variety of assets in the system makes it a good test-bed. The network includes bridges, viaducts and tunnels, as well as both street running track and ballasted track. In addition, given Pittsburgh's temperate climate, we have observed temperatures lower than -20ºC and higher than 35ºC.

We have placed sensors on two trains, each 27m long light rail vehicles weighing 40 metric tons made by the Spanish firm Construcciones y Auxiliar de Ferrocarriles S. A. (CAF) [1,2]. In our first instrumentation, shown in Figure 1a, we placed two uni-axial accelerometers inside the cabin of the train (Vibrametrics 5102) and a tri-axial accelerometer (PCB 354C03) on the central wheel truck. The central wheel truck is not powered and was selected to minimize electrical noise. We use National Instruments data acquisition hardware connected to a computer, which samples at 1.6kHz then logs the data to an external hard drive shown in Figure 1d and e. For position, we use a BU-353 GPS antenna and log position at 1Hz through the same data acquisition computer.

For our second instrumentation, we were able to improve upon the system from our first instrumentation. We used more sensors (2 uni-axial accelerometers (Vibrametrics 5102) and 2 tri-axial accelerometers inside the train (PCB 354C03), and 2 industrial grade accelerometers (IMI 623C00) on the central wheel truck) with a particular focus on sensors inside the train as seen in Figure 1b. Axle box accelerometers have been used by other researchers, but for long term monitoring, maintaining exposed accelerometers in such a high-shock environment is difficult [3,4]. We believe that installing sensors inside the cabin where they are protected from the elements and from high shocks will lead to lower-cost installation and maintenance. While the first system relied directly on power from the train, which can occasionally go out, our second system had a built in back-up battery for uninterrupted operation. Finally, our new system used both the same low-cost GPS as the first system (BU-353), as well as a high-end differential positioning system (SX Blue II + GNSS).

Besides accelerometer data and position data, we were able to gather additional information indirectly. To determine the environmental conditions, we used the train's GPS position to query environmental conditions such as temperature, wind and precipitation from a weather data-base called Forecast.io [5]. Finally, we have access to a weekly maintenance schedule from the operator of the light rail system, the Port Authority of Allegheny County.

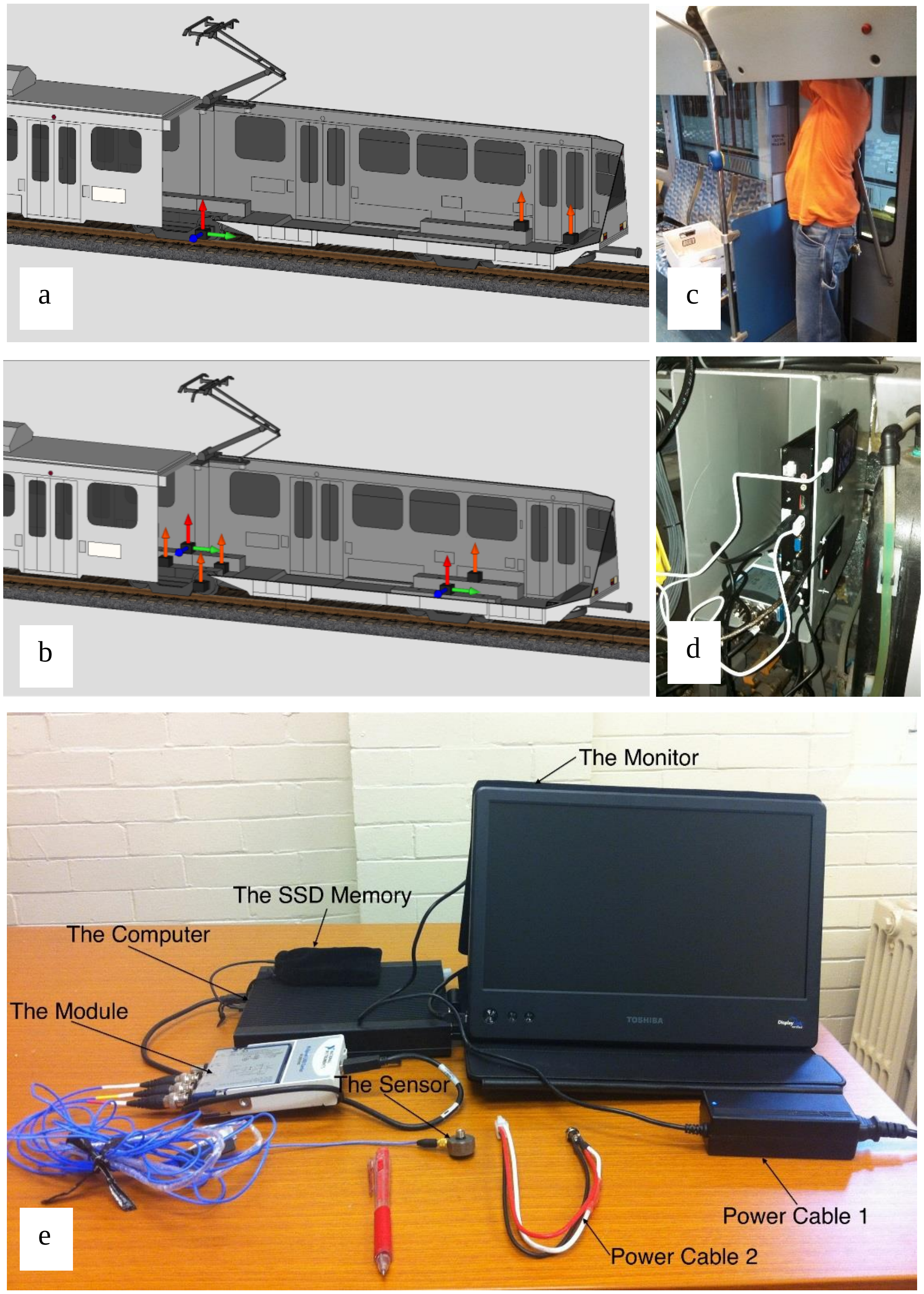

Figure 1: Sensor Locations for (a) the train instrumented in 2012 and (b) the train instrumented in 2015. The arrows indicate the axes of the acceleration measurement. (c) Installing wiring in the electrical cabinets (d) data acquisition computer located in electrical cabinet. (e) The computer and data acquisition system before installation, showing the external hard drive, one of the USB-powered data acquisition modules, and a tri-axial accelerometer (the sensor). The portable monitor is attached only when troubleshooting issues with the computer.

SHM Methodology and Results

Our ultimate goal is to detect damages in the tracks; however, there are numerous environmental and operational factors that make this difficult. Two main challenges of using a passenger train are that 1) the speed of the train varies and 2) the location of the train is not known precisely due to GPS error. This is highlighted in Figure 2a and b: in the first figure, the train stops at one station, and in the second figure the train stops at two stations.

In order to find changes in the tracks over time, we have found it useful to compare the data in the spatial domain (i.e. interpolated by position) and we have found signal energy in spatial domain to be robust to these sources of uncertainty. Although the change is not readily apparent in the raw data between Figure 2a and b, by looking at the signal energy in Figure 2c, the change in the track can be detected. We used change detection methods to detect these changes in an online manner [2].

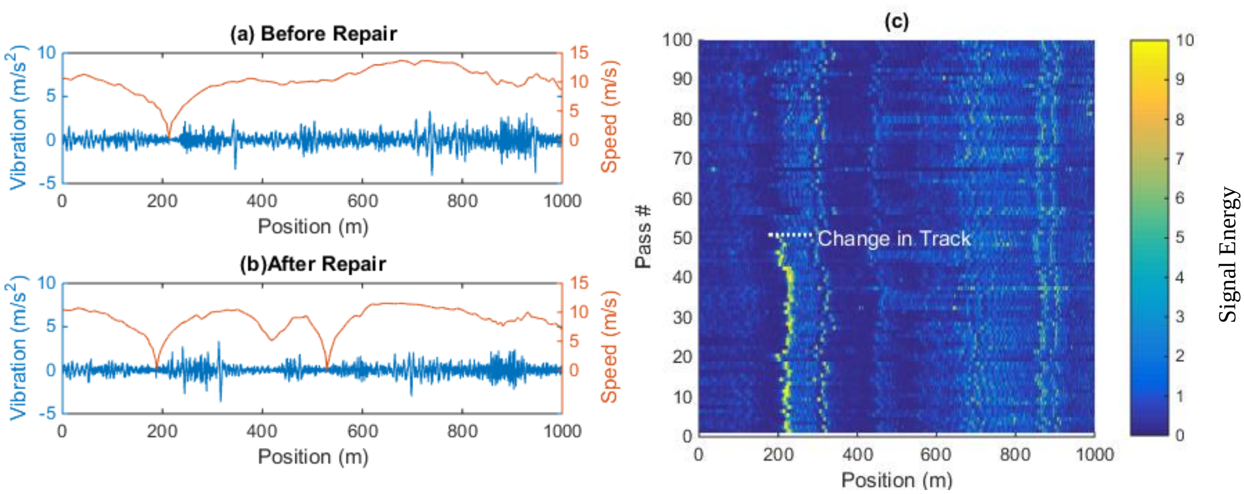

Figure 2 - Example data over a 1km region of track, both (a) before a repair and (b) after a repair. (c) Each horizontal line represents the signal energy feature for one pass, with 50 passes before the repair, and 50 passes after the repair. Notice the high energy area at 220m disappears after the repair (From Lederman et al. 2016 [2]).

Lessons Learned

There are numerous practical lessons we have learned over the course of this project. For example, ensuring a reliable power supply increased the amount of data collected, and protecting the sensors was important for long term monitoring. At one point, the tri-axial accelerometer started to produce anomalous data. It turned out the train had run over a deer. One of the benefits of this monitoring technique, is that each sensor interrogates the entire network, so it is easy to determine if the sensor is malfunctioning or if there has been sudden change in the structure of interest.

In this type of experimental work, it is of paramount importance to have ground-truth data for the validation of the system. Through the collaboration with the Port Authority of Allegheny County, we have been able to learn when maintenance activities occur on our network, and detecting this maintenance events has allowed us to validate our system. Although we know roughly the type of work performed, more details about precisely what is done would be helpful in labeling the track condition.

Thus far, we have been able to detect several types of track changes, and have been able to do so using unsupervised change-detection approaches. Given the low-cost nature of monitoring from passenger trains, this could be an attractive way to monitor entire infrastructure networks. Our data-driven approach means that modeling the complex assets along the train's path is not required. This technique could easily scale to larger infrastructure networks, and the rise of connected vehicles may reduce the barriers to collecting more data about train-track interaction, or more broadly, vehicle-infrastructure interaction.

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References

[1] G. Lederman, H. Noh, J. Bielak, Rail-infrastructure monitoring through the dynamic response of a passing train, in: IWSHM, Stanford, CA, 2015. http://dpi-proceedings.com/index.php/SHM2015/article/view/844/844 (accessed November 9, 2015).
[2] G. Lederman, S. Chen, J.H. Garrett, J. Kovačević, H.Noh, J. Bielak, Infrastructure monitoring from the dyanamic response of an operational train, Submitt. J. Mech. Syst. Signal Process. (2016).
[3] M. Bocciolone, A. Caprioli, A. Cigada, A. Collina, A measurement system for quick rail inspection and effective track maintenance strategy, Mech. Syst. Signal Process. 21 (2007) 1242–1254. doi:10.1016/j.ymssp.2006.02.007.
[4] J. Real, P. Salvador, L. Montalbán, M. Bueno, Determination of Rail Vertical Profile through Inertial Methods, Proc. Inst. Mech. Eng. Part F J. Rail Rapid Transit. 225 (2011) 14–23. doi:10.1243/09544097JRRT353.
[5] Forecast Blog: The Forecast Data API, (n.d.). http://blog.forecast.io/the-forecast-data-api/ (accessed September 26, 2014).