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Track monitoring from the dynamic response of a passing train: A sparse approach

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ABSTRACT

Collecting vibration data from revenue service trains could be a low-cost way to more frequently monitor railroad tracks, yet operational variability makes robust analysis a challenge. We propose a novel analysis technique for track monitoring that exploits the sparsity inherent in train-vibration data. This sparsity is based on the observation that large vertical train vibrations typically involve the excitation of the train's fundamental mode due to track joints, switchgear, or other discrete hardware. Rather than try to model the entire rail profile, in this study we examine a sparse approach to solving an inverse problem where (1) the roughness is constrained to a discrete and limited set of "bumps"; and (2) the train system is idealized as a simple damped oscillator that models the train's vibration in the fundamental mode. We use an expectation maximization (EM) approach to iteratively solve for the track profile and the train system properties, using orthogonal matching pursuit (OMP) to find the sparse approximation within each step. By enforcing sparsity, the inverse problem is well posed and the train's position can be found relative to the sparse bumps, thus reducing the uncertainty in the GPS data. We validate the sparse approach on two sections of track monitored from an operational train over a 16 month period of time, one where track changes did not occur during this period and another where changes did occur. We show that this approach can not only detect when track changes occur, but also offers insight into the type of such changes.

1. Introduction

Monitoring track geometry is essential to ensuring the safe operation of rail-infrastructure, yet current inspection techniques require track downtime [1,2]. Monitoring railroad track geometry with in-service vehicles could reduce required track downtime while providing more continuous information than using dedicated inspection vehicles [3–7]. Decreases in the cost of sensing equipment have made monitoring tracks from in-service vehicles economical while recent advances in analytical techniques have made processing the collected data feasible.

Three main types of sensing technology have been proposed for in-service trains: optical sensors (using lasers) [8,9], magnetic flux sensors (also called Foucault currents or Eddy Currents) [10,11], and inertial sensors (using accelerometers)

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[3–6,12–20]. Optical sensors are used widely on track geometry cars, however they stop functioning if the lens becomes dirty. They require constant cleaning and maintenance, and thus are not appropriate for long term-monitoring from in-service vehicles [21]. Foucault current monitoring requires a magnetic coil placed close to the rail, making the coil vulnerable to objects along the track. Given the drawbacks of other sensing technologies, inertial sensors have become the most popular approach. The sensors are often placed on the axle box [3–5], but can be placed anywhere on the train even inside the cabin [18]. The challenge in using accelerometers lies in analyzing the collected data.

There have traditionally been two approaches to analyzing train-based accelerometer data: using an explicit model or an implicit model. Explicit models attempt to determine the precise track profile, typically using *a priori* knowledge of the train and its suspension system to solve an inverse problem [15,18]. For each pass over the tracks, the track profile is estimated; deterioration in the tracks can be detected as changes in the profile. Implicit models derive a feature from the accelerometer data which often serves as a proxy for track geometry or roughness. In these models, deterioration is detected when the values of the features change. Notable implicit models have been based on wavelets [3,12,22,23], the Short Time Fourier Transform [4], signal standard deviation [5], and signal energy [6,24].

Implicit models tend to be more robust and may allow for the detection of a change, but as the feature is not directly representative of the track state, they often do not provide insight into the nature of the change. Explicit models can estimate the track profile before and after a change so that the mechanism of the change could in theory be determined. However, to our knowledge, this technique has not been used for long-term monitoring [15,18]; the instability in solving the inverse problem directly makes consistently determining the track profile a challenge.

In this paper, we propose a novel approach to approximate the track profile. As the dynamic response of the train contains information both about the train and about the tracks themselves, we decompose the vibration signal in an effort to separate these sources. To do so, we solve an inverse problem which determines the train's main dynamic properties and the profile of the track.

Solving such an inverse problem can be unstable; we constrain the problem to make it tractable. The first constraint comes from the observation that the train's suspension is typically activated by a few large bumps in the track. Thus we aim to find these discrete "bumps" and do so by enforcing sparsity in the estimated track profile.

The second constraint pertains to the characterization of the train system. We know the approximate properties of the train *a priori*, but these can change over time depending for example, on passenger loading. Thus we want to solve for train properties from the data, but doing so directly can provide noisy results. In a previous study [6], we found that the train's fundamental mode dominates its response. So we limit the problem to characterizing this fundamental mode which can be represented as a single degree-of-freedom damped oscillator. By modeling one part of the train vibration, we are able to reduce some of the train dependent variables in the signal.

In some ways, this technique resembles the explicit model mentioned earlier. We solve an inverse problem that provides information about both the train and the tracks. However, due to the sparse constraints, the resultant track profile is quite different from the true profile. In this regard, the technique resembles the implicit model more closely. The resultant sparse track profile can be thought of as a feature indicative of track state. We can explore the merit of this sparse constraint by testing how closely changes in the sparse profile match changes in true track profile. Compared to other features, like wavelets, the sparse profile provides greater insight because it can show the direction in which the track has changed, for example either settlement or uplift.

Enforcing sparsity in the track has a number of benefits [25–28]: (1) the problem is constrained so some properties of the train system can be found without making the problem ill-posed, (2) the discrete bump locations can be used to locate the train, overcoming GPS error, and (3) the size of the bumps are useful low-dimensional features for detecting the significance of changes in the track.

(1) We characterize the train system while constraining it to the physics of the problem. We require that the transfer function correspond to a simple damped oscillator. When enforcing this condition, the parameters found relate to the stiffness and damping ratio of the main suspension between the wheel truck and the train chassis. This makes physical sense because when a large bump in the tracks excites the train, the largest displacement is in the primary suspension, and we require that the approximate roughness models only large bumps. Unlike previous methods in which the parameters of the train must be known *a priori*, our approach solves for the train properties in the process of solving for the track profile.
(2) We locate the train using a GPS antenna, but due to overhead interference and other factors, the position-error can exceed 10 m. This level of error makes it challenging to compare data between passes. Train localization has been studied in the literature primarily for collision avoidance [29]. Some researchers have proposed using track features to help localize trains in this context [30,19]. For monitoring purposes, precise localization is of paramount importance. Enforcing sparsity facilitates localization because the position of the train can be found relative to the sparse bumps.
(3) Finally, the size of the bumps can be used to determine whether the tracks have changed or deteriorated. If a complete rail profile were to be calculated, the high dimensionality of the data (proportional to track length) would make robust change detection more challenging; the low-dimensionality of bump height as a feature simplifies change detection, as will be shown in Section 4.