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IDENTIFICATION OF MOVING LOADS VIA ℓ_1-CONSTRAINED SOLUTIONS

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1 INTRODUCTION

Indirect identification of moving loads based on the measured response is one of the crucial problems in structural health monitoring. It is important in automated assessment of structures and pavements, in traffic monitoring and control, and as a prerequisite for structural control. As such, it has been intensively researched [1]. An important difficulty is that a moving load can excite a very large number of structural Dofs, which all have to be taken into account in the identification procedure based on measurements of a much more limited number of sensors. A straightforward formulation yields thus an underdetermined problem with an infinite number of solutions. Therefore, in most of the approaches so far, the solution space is significantly limited by the assumption that the load corresponds to a single vehicle moving at a constant velocity, which excludes loads of a more general nature (e.g., multiple loads).

However, instead of limiting the solution space, it can be noted that in practice moving loads are sparse in time and space, which fits the framework of compressed sensing [2]. Such an a priori knowledge of sparsity is typically expressed by limiting the ℓ_1 norm of the solution [3]. To our knowledge, although used in other contexts, the concept has not been applied so far for identification of moving loads. The approach is tested in a numerical example with 10% rms measurement noise. Experimental work is in progress.

2 THE INVERSE PROBLEM

The structure is assumed to be linear. With the assumption of zero initial conditions, responses of linear sensors can be stated as

$$\mathbf{a} = \boldsymbol{\mathcal{B}}\mathbf{f}, \tag{1}$$

where the vector $\mathbf{f}$ is the excitation of the moving load(s) and $\boldsymbol{\mathcal{B}}$ represents the (discrete or continuous) form of the convolution operator. In practical cases the length of the excitation vector $\mathbf{f}$ is much larger than the length of the measurement vector $\mathbf{a}$, so that there are more unknowns than equations. To attain uniqueness, the a priori knowledge about the sparsity of the load is used. It is expressed by augmenting the norm of the residuum with the ℓ_1 norm of the solution to form the following objective function to be minimized [3]:

$$F(\mathbf{f}) = \|\mathbf{a} - \mathbf{B}\mathbf{f}\|^2 + \alpha\|\mathbf{f}\|_1, \tag{2}$$

where α plays the role of the weighting coefficient.

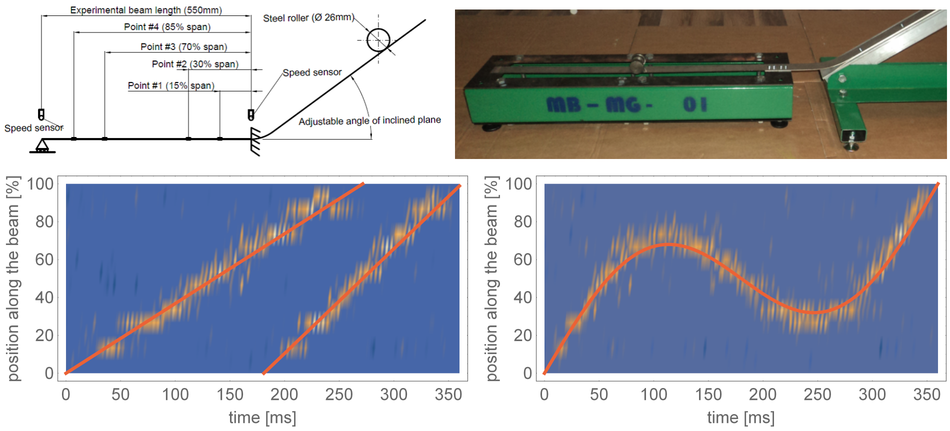

Figure 1: The modeled stand; numerical results at 10% rms simulated measurement noise.

3 NUMERICAL EXAMPLE

An experimental stand is in construction, see Fig. 1 (top). It consists of a flexible simply supported beam excited by a steel roller, which is accelerated on an inclined plane to obtain various rolling speeds. The strain response is measured in four points of the beam. For simulations, a finite element model of the beam (21 elements) is used with the respective geometric, material and excitation parameters. To simulate the response, the moving load is transferred to the Dofs using the element shape functions. For the purpose of identification, it is assumed to vertically excite the beam in 16 equally spaced points. Strains simulated in the four points are contaminated with an uncorrelated Gaussian noise at the level of 10% rms. There are thus 4 times more unknowns than equations (measurements) in (1), and incorporation of the criterion of sparsity into (2) is necessary to obtain unique solutions.

Two exemplary results computed using Wolfram Mathematica and L1packv2 [4] are shown in Fig. 1 (bottom) in the time–space plane. The continuous lines correspond to the simulated actual trajectories of the loads, and the density plots represent the identification results. A good qualitative agreement can be observed.

4 ACKNOWLEDGMENTS

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