SMART MOBILE PLATFORM FOR MODEL UPDATING AND LIFE CYCLE ASSESSMENT OF BRIDGES

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INTRODUCTION

Mobile sensing is an alternative paradigm that offers numerous advantages compared to the conventional stationary sensor networks. Mobile sensors have low setup costs, collect spatial information efficiently, and require no dedicated sensors to any particular structure. Most importantly, they can capture *comprehensive spatial information* using few sensors. The advantages of mobile sensing combined with the ubiquity of smartphones with the internet of things (IoT) connectivity have motivated researchers to think of *cars+smart phones* as large-scale sensor networks that can contribute to the health assessment of structures. Working with mobile sensors has several challenges. The signals collected within a vehicle's cabin are contaminated by the vehicle suspension dynamics; therefore, the extraction of bridge vibration from signals collected within a vehicle is not an easy task. Additionally, mobile sensors simultaneously measure vibration data in time while scanning over a large set of points in space, which creates a different data structure compared with fixed sensors. Since collected data are mixed in time and space, they contain spatial discontinuities. When these challenges are addressed, mobile sensing is a promising data resource enabling crowdsourcing and an opportunity to extract information about infrastructure conditions at an unprecedented rate and resolution (Matarazzo and Pakzad, 2013). In this regard, this project proposes deep learning frameworks specific to mobile sensing to perform input force identification in vehicles and learn underlying governing equations of a dynamic system from data that will circumvent the development of high-fidelity models.

METHODOLOGY

Due to the nonlinearity and complexity of realistic dynamic systems such as vehicles, an approach was needed that accomplishes the input estimation with no baseline model or restrictive assumptions. In this project, a recurrent neural network (RNN) framework was developed that is able to learn the nonlinear input-to-output transformation of dynamic systems and then exploit this information to deconvolve the output. Figure 1 presents a schematic overview of the inference using the proposed framework. In this figure the neural network is represented as an RNN block with an inverted L-shaped input; at each time step the RNN block processes the input and output values inside the L-shaped binder to predict the one-step backward estimation of the input. This process is repeated until the maximum possible length of the input signal is estimated. In this framework, the input signals are associated to the tire contact point (CP) of a vehicle and cabin signals are systems' outputs. Note that the figure depicts a single-input single-output (SISO) case in which the number of response channels is equal to one. However, in multi-degree-of-freedom (MDOF) systems, the network dimensions adapt accordingly with no substantial change in the proposed structure or the pipeline.

Partial differential equations (PDEs) are widely adopted in a plethora of science and engineering fields to explain a variety of phenomena such as heat, diffusion, electrodynamics, fluid dynamics, elasticity, and quantum mechanics, to mention a few. This is primarily due to their ability to model and capture the behavior of complex systems as well as their versatility. However, solving PDEs is far from a trivial task. Often incredible amounts of computing power and time are required to get reasonable results, and the methods used can be complicated and highly sensitive to the choice of parameters. The rapid development in data sensing (collection) and data storage capabilities provides scientists and engineers with another avenue for understanding and making predictions about these phenomena. The massive amounts of data collected from highly complex and multi-dimensional systems have the potential to provide a better understanding of the underlying system dynamics. In this project, inspired by finite-difference approximations and residual neural networks (He et al. 2016), the authors propose a novel neural network framework, finite difference neural networks (FD-Net), to learn the governing partial differential equations from trajectory data and iteratively estimate future dynamical behavior.

Mimicking finite-difference approximations, FD-Net employs "finite-difference" block(s) (FD-Block) with artificial time steps to learn first-, second- and/or higher-order partial derivatives, and thus learn the underlying PDEs from neighboring spatial points over the time horizon.

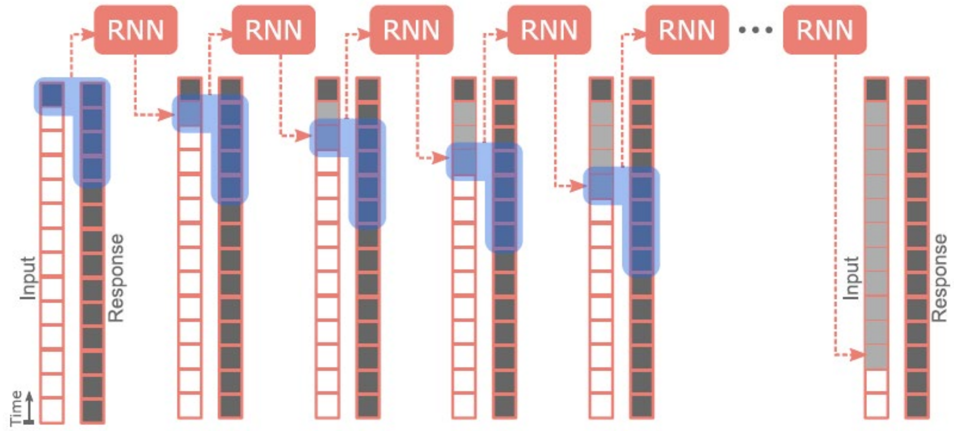

Figure 1. Schematic diagram of the input estimating network.

DATA SUMMARY

To demonstrate the efficacy of the proposed network, an experiment was designed and conducted in order to estimate the input of a real-world vehicle using its cabin acceleration data. In this experiment, the data were collected in two locations: inside the vehicle cabin and in proximity to the CP. Note that the actual vehicle's CP was practically inaccessible for a sensor device. Therefore, the lower control arm was selected as a feasible location, and a manually assembled sensor bundle was attached to that location.

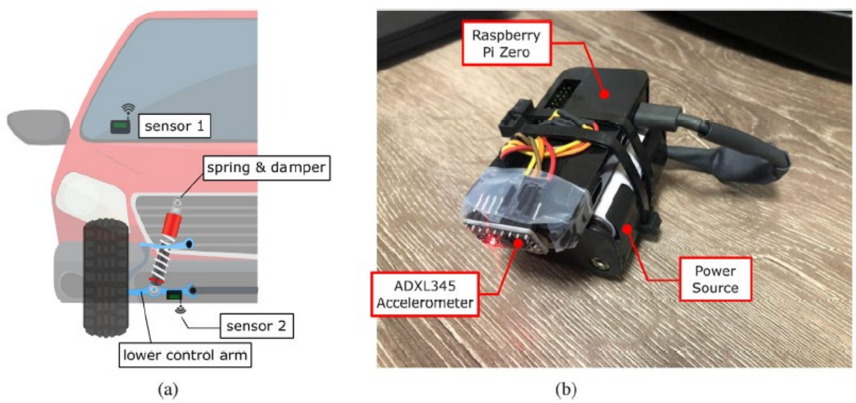

Figure 2. (a) Schematic view of the car and sensor layout; (b) sensor setup used in the experiment: the main board is a Raspberry Pi zero and the sensing device is an ADXL345 accelerometer.

The sensors were wirelessly communicating with a computer, which was held by the operator in the passenger's front seat. The cabin sensor was attached to the dashboard of the vehicle. The sensor layout is presented schematically in Figure 2(a). As shown in the figure, sensor 2 was mounted on the lower control arm, which was found to be a suitable location for the vehicle input data collection and was not affected by the suspension springs. The arm is a solid beam attached to the rim and is located right before the spring and the shock absorber on the load path from the tire to the vehicle cabin. The sensor bundle used for vehicle data collection is shown in Figure 2(b) (similar configuration is used in both locations). The bundle consists of three components: (1) a Raspberry Pi zero board, (2) an ADXL345 accelerometer, and (3) a power source. The Raspberry Pi was selected for its data processing and storage functionality as well as its low cost, easy programming, and wireless connectivity. ADXL345 is a three-axis accelerometer that is compatible with Raspberry Pi and collects data at a high rate. The acceleration range and sampling frequency can be tuned based on the application and required accuracy. To select these parameters, a lab-scale experiment was conducted on a single-degree-of-freedom system and the accuracy of the neural network predictions was compared for data collected from different sensor settings. Based on this preliminary study, the sampling frequency of 500 Hz and acceleration range of ±16.0 g were set for the final experimental trial. Note that the adjusted frequency is an upper bound for the sensor, and in practice the sensor collects data with nonuniform time intervals and lower rates. This was found to be affected by the throughput rate of the Raspberry Pi and its wireless communication. For the road test, a KIA Forte 2020 was equipped with the sensor sets. According to the vehicle's official specifications, the vehicle suspension is equipped with nonlinear suspension systems in front and rear positions. In particular, the suspension system consists of MacPherson strut and twin tube shock absorbers, both of which exhibit nonlinear behaviors. The instrumented vehicle was driven over roads with different roughness conditions, including recently paved, poor condition, and gravel roads near the Lehigh University campus. In total, 23 scans of 50,000 samples were collected. The vehicle speed was mostly kept within 10–12.5 mph; however, in rare situations of traffic congestion in the testing area, the speed varied. The collected data were then preprocessed for training, which included the following steps: (1) signal resampling in order to even the time intervals between samples, (2) signal filtering using a band-limited filter, and (3) down-sampling to 100 Hz. Filtering and down-sampling steps reduce high-frequency noise as well as measurement drifts in the collected signals. After preprocessing, the signals were normalized linearly using the previously explained approach. This approach for normalization was found to yield better performances compared to other conventional methods (e.g., based on maximum absolute value). The training process of the real-world vehicle experiment was the same as the previous case studies. From 23 scans, 10, 1, and 12 samples were randomly picked for training, evaluation, and testing, respectively. Note that the majority of data were kept for testing for better performance assessment.

For demonstrating the efficacy of FD-Net, the heat equation was used as a case study. The performance of the proposed algorithm was compared to the closed-form solution, and solution estimated using a forward Euler approach.

EVALUATION RESULTS

To evaluate the performance of the network for input estimation, the reconstructed input signals for one of the testing samples are presented in Figure 3. This generally confirms the efficacy of the input estimation in all three axes. The original input signal is highly nonstationary, which is caused by irregular road conditions (such as road bumps or potholes) that complicate the process of learning. Yet, the trained network successfully estimated the overall patterns. More details and results can be found in Eshkevari et al. (2022).

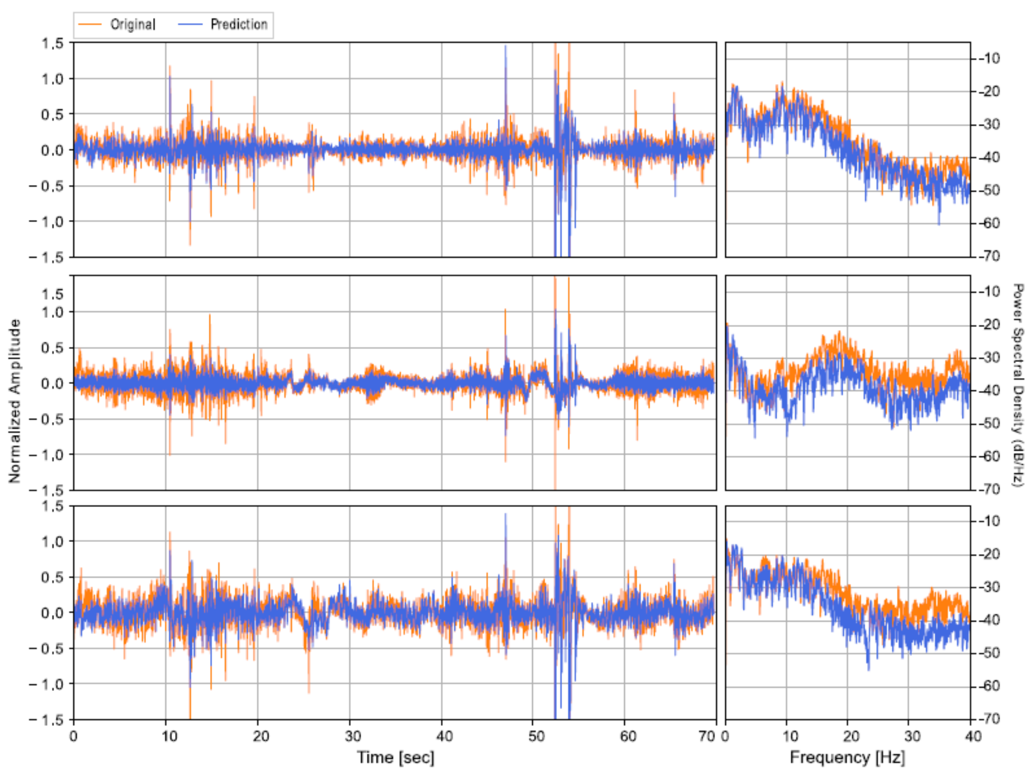

Figure 3. Vehicle input signal predictions in three axes.

FD-Net was tested using the heat equation. The proposed framework's performance was compared to a forward Euler solver. Furthermore, the proposed algorithm was trained using two different optimizers. The popular Adam optimizer with two different learning rates and 10,000 iterations was used. It is shown that training time can be significantly reduced and the accuracy of the solutions can be drastically improved by using a second-order method. Specifically, second-order

Hessian-Free method, Trust-Region (TR) Newton Conjugate Gradient (CG) was employed. The TR method was trained with only 100 iterations. Figure 4 shows that the TR-based approach yields the highest accuracy. More details and results can be found in Shi et al. (2020).

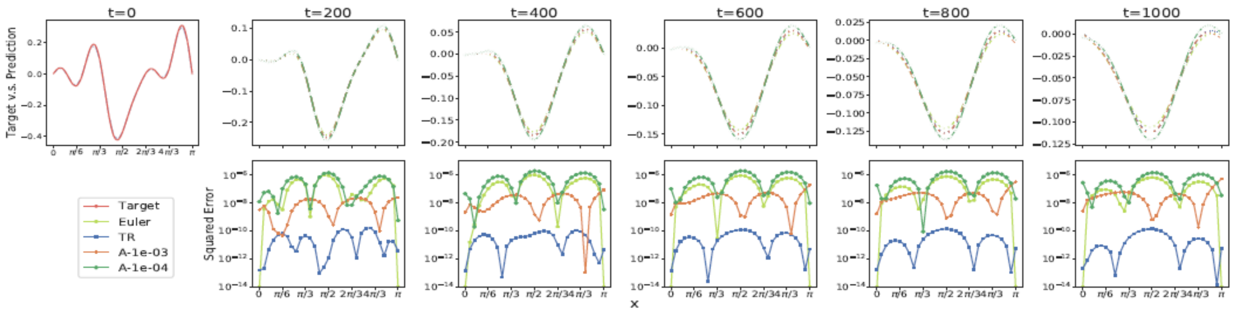

Figure 4. Sequence of predictions along with the squared errors for the forward Euler approach, Trust region-based optimizer approach (TR), and traditional Adam optimizer approach (A followed by the learning rate).

CONCLUSION AND IMPLEMENTATION

In this project we demonstrate the efficacy of a DNN-based framework for estimating input forces for a vehicle, thus deconvolving the effects of vehicle dynamics in signals sensed from the cabin of a vehicle. The proposed framework demonstrated its efficacy for both numerical and field data. Furthermore, a DNN-based network was developed that can learn the underlying governing partial differential equation of dynamic systems. Both of these frameworks will help facilitate a mobile sensing paradigm for bridge monitoring.

In the future, the research team plans to further generalize the DNN framework and validate the data collection API by pursuing the following directions:

- Harness the power of further advancements in deep learning that will allow for modeling of the various spatiotemporal dependencies of the problem.
- Augment deep learning frameworks with more involved physical principles associated with the problem at hand to enhance performance and facilitate interpretability from a physical standpoint.

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