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AN EVOLUTIONARY HYBRID APPROACH TO IDENTIFY MULTIBODY SYSTEMS WITH PARTIALLY KNOWN PHYSICS

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1. INTRODUCTION

Although the recent development of sensing techniques and machine learning approaches have contributed to the motion prediction and simulation of dynamical systems, the cost of data acquisition is still prohibitive. There also are critical locations of mechanisms inaccessible for instrumentation [1]. Subsequently, one is encountered with partial information from a physical identity, resulting in inaccurate training of neural networks. In addition, a feasible challenge in working with multibody systems is that one knows the physics of a given system partially due to associated complexity and nonlinearity, and lack of information. Linking the known physics to data-driven models to compensate for unknown physics can be helpful such that physical equations guide the training towards the right solution quickly by confining the space of admissible solutions, reducing discrepancies between a fully known physics and an incompletely known one [1, 2]. This approach improves predictions and mitigates the training issue of neural networks with limited data [3]. However, this hybrid method of physics-based simulation and deep neural network can result in a black-box function for the unknowns in multibody systems, which are not physically interpretable and generalizable.

Combining statistical learning concepts with classical approaches in applied mechanics and mathematics, Schmidt and Lipson [4] used the genetic algorithm to distill motion equations from experimental data, which are interpretable. Brunton et al. also developed a popular approach for the model discovery of dynamical systems, the so-called SINDy [5]. As the latter is limited to a function dictionary built by a user, Askari and Crevecoeur suggested an evolutionarily symbolic regression method to generate an adaptive function dictionary [6]. In this study, we intend to extend the algorithm in [6] and develop an evolutionary hybrid procedure of physics-based modeling and symbolic regression procedure for the model discovery of an unknown subsystem of a multibody mechanism, Fig. 1. The governing equations of the subsystem can be identified in an interpretable fashion. The applications of this strategy encompass digital twins, system identification, control, and condition monitoring.

2. MATHEMATICAL MODELING

A subsystem in a multibody system is considered unknown. This subsystem and the rest of the given multibody mechanism exchange data forth and back over the course of being in service. From a modeling viewpoint, the system can be divided into two distinct sections, namely Sub A and B. The former is fully modelled but the other is not. Our remedy for system identification is to construct a co-simulation framework, in which a Gauss-Seidel coupling scheme is integrated, linking two physics-based solvers accounting for either subdivision. A governing equation of Sub B is built from a set of candidate functions and mathematical operators by an evolutionary sparse data-driven algorithm [6]. Genetic programming generates symbolic function expressions, $\mathbf{\Theta}$, randomly and a sparse Ridge regression approach obtains unknown coefficients in motion equations. Inputs of the generated functions are observed states of the mechanism. The data Sub B sends to A is designated by data vector $\mathbf{z}$, Fig. 1.

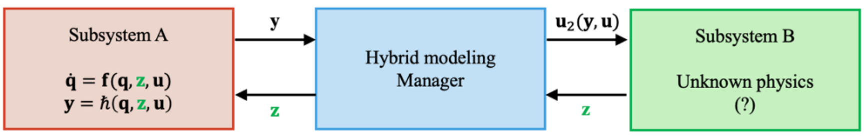

Fig. 1. Subsystem A is coupled to subsystem B in a hybrid model setup.

The exchange data $\mathbf{z}$ is considered the solution of the dynamic system B, which can be approximated by a set of test functions. The suggested evolutionary method not only explores candidate functions that represent the data well but also finds how much each candidate function contributes into the good solution of motion equations of Sub B. The latter is quantified by the coefficients $\boldsymbol{\xi}$ appearing in $\mathbf{z} = \mathbf{\Theta}\boldsymbol{\xi}$. The error of this approximation is calculated using Ridge regression method, for which the cost function is decided as

$$J(z) = \|\mathbf{f}(\mathbf{x}, \mathbf{u}, \mathbf{z}) - \mathbf{d}\|_2^2 + \lambda\|\boldsymbol{\xi}\|_2^2, \quad \mathbf{z} = \mathbf{\Theta}\boldsymbol{\xi} \tag{1}$$

One needs to optimize this objective function J for unknown coefficients $\boldsymbol{\xi}$. Assuming a dynamic system governed by $\dot{\mathbf{q}} = \mathbf{f}(\mathbf{q}, \mathbf{z}, \mathbf{u})$ and using a gradient descent procedure and a line search method. The coefficients for each element in the population is determined and a fitness measure evaluates respective fit-to-data error and parsimony of the generated equation.

3. RESULTS AND DISCUSSION

Using the developed algorithm, the governing equations of lateral forces of vehicle wheels are discovered based on the vehicle dynamic responses collected by IMU. The algorithm obtains the final formulation less than twenty minutes. In each experiment, one experimental dataset is left out as the testing data and the algorithm is run using the remained datasets for training. Function and terminal sets chosen in this experiment are {+, ×, ÷, sin, sqrt, abs, sign, arctan, exp, int} and $\{t, x_i, c\}$, respectively, where int represents the time integration and the subscript i belongs to the set of $\{1,\dots,6\}$ corresponding to rear-wheel sideslip angle, longitudinal speed, steering wheel angle, lateral vehicle speed, yaw rate, front-wheel sideslip angle, respectively. The population size is 400 and the algorithm continues to regenerate populations until the fitness measure converges. The code keeps breeding the next generations just more than 200 times. The outcomes associated with testing dataset are plotted in Fig. 2. It implies that lateral forces are dependent on yaw rate x_5 and steering wheel angle x_3 for these sets of data. Respective distilled formulations are given in Eq. (2). The approximated lateral forces can be written as a span of function subspace D.

$$D = \left\{x_5, \int x_3\, dt\right\} : \bar{z} \subset D. \tag{2}$$

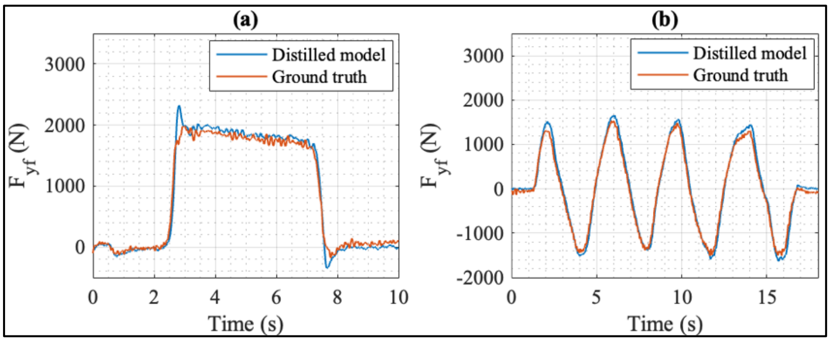

Fig. 2. Lateral force of the front wheel: (a) step steering maneuver; (b) sine steering maneuver 0-25 Hz.

Another demonstrative example considered in this research work is a spring-mass system with a friction model, a hyperbolic tangent function of sliding velocity. It is assumed that friction model is unknown. The function that the algorithm reveals is displayed in Fig. 3, and one can argue that the approximated solution complies quite well with the original one.

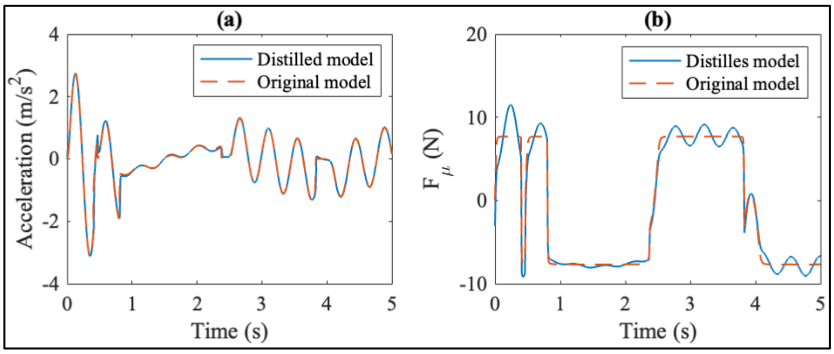

Fig. 3. A comparison between the discovered and original friction models and resulting dynamic responses.

4. CONCLUSION

This study suggested an evolutionary hybrid approach that can discover interpretable formulations associated with the physics of an unknown subsystem in a mechanism of interest. The multibody system was divided into two subsystems, which were later linked together through a hybrid framework. The genetic programming generated symbolic function expressions and sparse regression approaches obtained the unknown coefficients of each function term in the equations of motion. This suggested approach unraveled the governing equations of lateral forces developed onto vehicle wheels merely from dynamic responses. The methodology was also evaluated on a synthetic data associated with a spring-mass system with friction to discover the friction relationship. The model was promising and can be used for system identification, simulation, and digital twins of mechanical systems. A model limitation can be foreseen if states that contribute to the dynamics of an unknown subsystem were not observable, respective distilled relationships may be erroneous to some extent and not be utterly representative.

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