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Simulation of mechanism with frictional effects combining physical models and machine learning regression models

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Within the design process of a new machine it is necessary to harmonize the properties of mechanical parts, joints, sensors, actuators and control algorithms. Kinematic joints are essential components of the machine structure. Especially in various robotic devices with the required large range of motion and at the same time high accuracy, they are difficult to replace. Kinematic joints are necessary e.g. also for active multi-dimensional absorber investigated in CTU [4] in order to allow relatively large motions which bring possibility of non-linear behaviour. Usage of flexible pseudo-joints is only possible for small motions and in addition it brings many other problems, such as fatigue damage, problematic integration with accurate sensor of relative motions, etc. The ability to overcome the harmful effects of imperfections and friction in the joints of machine is one of the key issues of computed aided design. Although the use of virtual prototypes or digital twins is an established part of mechatronic design, the sufficiently reliable modelling of the joint imperfections and friction effects is still an open problem. Unfortunately, the late detection of insufficient suppression of these phenomena often leads to the need for a complete overhaul of the machine concept almost from the beginning.

Research and ways to model and compensate these nonlinearities are very current, for example, the use of LuGre models [3] and their combinations with advanced observers [5] can be mentioned. For detailed research of suitable models of passive effects, an experimental stand equipped with accurate motion measurement is important for a detailed comparison of the real mechanism and its models. An experimental demonstrator of above mentioned absorber was used for the research purpose. It includes three controlled legs with voice-coil actuators, linear ball bearings, accurate built-in linear encoders and precise revolute/spherical joints.

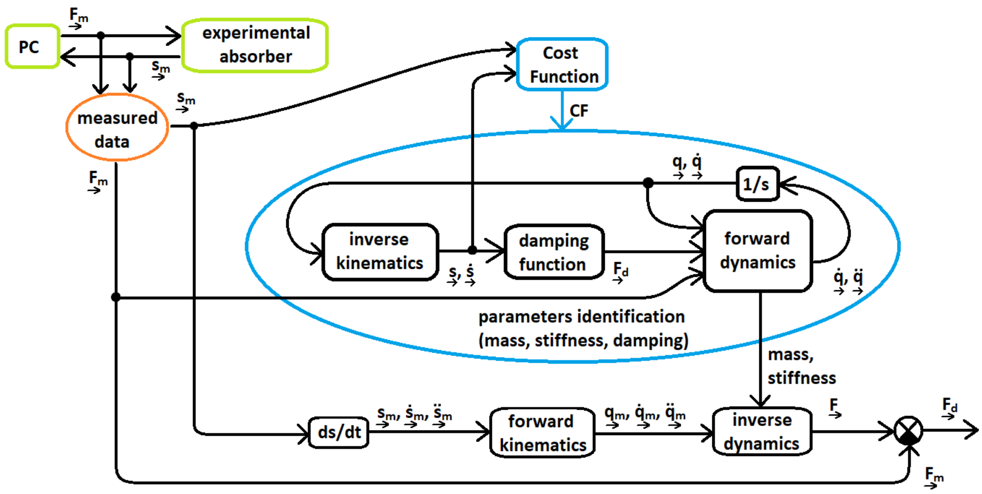

Fig. 1. Scheme of identification of LuGre models and other parameters by optimization

$$
\begin{aligned}
F &= \sigma_o z + \sigma_1 \dot{z} + \sigma_2 v \\
\dot{z} &= v \cdot \left(1 - \frac{\sigma_o z}{g(v)} sgn(v)\right) \\
g(v) &= F_d + (F_s - F_d) e^{-(v/v_{Stribeck})^{\gamma}}
\end{aligned}
\tag{1}
$$

Fig. 1 schematically shows the procedure used to identify the mechanism model equipped with well known LuGre models (1) of passive effects in joints based on training and testing experiments. During these identifications, the repeatability of the results and the degree of uncertainty of the obtained models were also determined.

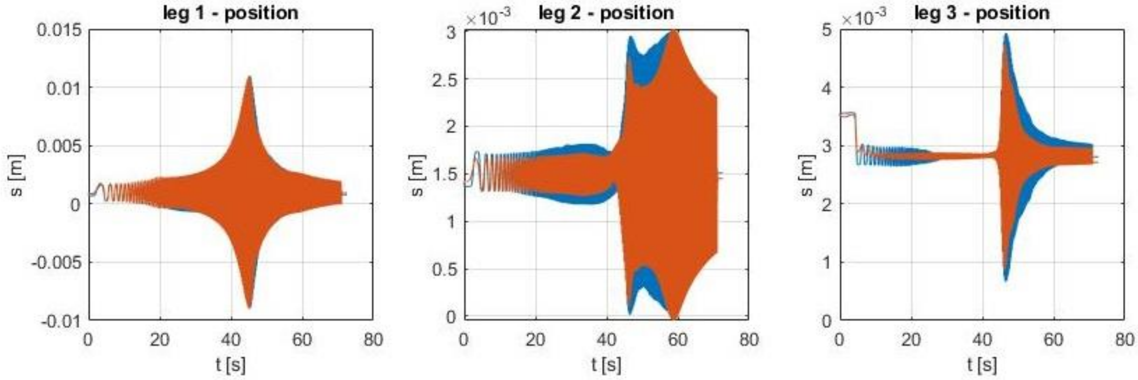

Fig. 2. Reality-model comparison after identification of LuGre models and other parameters

As can be seen from the Fig. 2, even after the optimization tuning of LuGre model parameters in kinematic joints and other mechanism parameters, the match between experiment and simulation is not perfect, especially for the second leg of the mechanism. This is due to significant frictional and adhesive effects.

Therefore, it is advisable to look for new auxiliary tools for supplementing the physical models and improving the accuracy of simulation and/or prediction with respect to reality. To further improve the model of mechanisms with frictional effects two state of the art machine learning methods are used – deep learning [2] and XGBoost [1]. The input data are divided into the training set and testing set. The training set is used for fitting the model while the model performance is evaluated on the testing set. The values of key hyperparameters of both methods are tuned to further increase the predictive power of the models.

Acknowledgement

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