Predicting Impact Responses of the Spacecraft Soft Landing on the Airbag System by Simulation-Based Deep Learning Models

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June 6, 2024

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Abstract

With the trend of increasing the capacity of the spacecraft, it will be subjected to severe shock vibration when landing on Earth with a certain velocity. To ensure the safety of the internal astronauts and protect scientific equipment from damage, it is necessary to adopt the airbag landing system (ALS) for impact attenuation [1-3]. As shown in Fig. 1, multiple airbag assemblies are installed under the bottom of the CM to form the cushion system, each of which consists of a main venting airbag and a non-venting anti-bottom airbag. The impact response characteristic of most concern is the acceleration time history, especially the acceleration peak. However, variable initial landing conditions and the complicated system configuration make impact response prediction difficult and time-consuming. With the development of artificial neural networks, deep learning can be utilized to create the surrogate model with limited training examples obtained through simulations [4]. This study proposes simulation-based deep learning models for fast predicting the impact accelerations of the spacecraft during soft landing on the complex airbag system.

The finite element model is constructed to generate the dataset with multiple inputs and outputs by using the commercial software LS-DYNA. The vertical impact velocity v_y , the horizontal impact velocity v_x , the initial pressure p_m of main airbags, the initial pressure p_{ab} of anti-bottom airbags, and the overload threshold g_v for venting are selected as input features of the dataset. A total of 100 simulations are performed by randomly selecting values from the input space (one case terminated early for computation divergence). The simulation time is 0.3s. Each simulation gives 3 local impact acceleration time histories of the spacecraft: the local y-axis acceleration, the local x-axis acceleration, and the local z-axis angular acceleration. Then we filtered these acceleration curves and sampled 100 data points uniformly for each curve.

We first trained separate MLP models for different impact accelerations (Fig. 2). All the data points are shuffled and no longer arranged in a time series. Then the dataset is split into training, validation, and testing sets with a 90%, 5%, and 5% proportion, respectively. After training and hyperparameter identification, we evaluated the deep learning models on independent curves from the dataset. The relative errors between the predicted and experimental values of the maximum localized y-axis acceleration are within 10%.

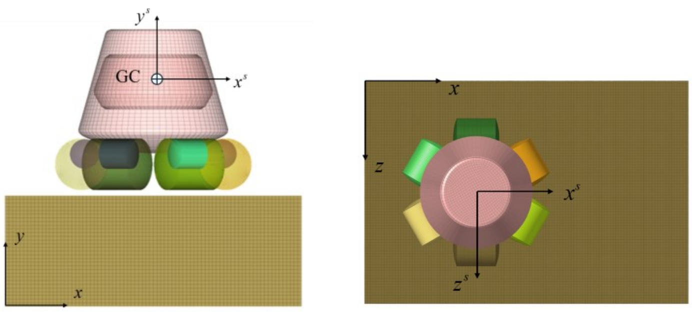

Figure 1: The configuration of the complex airbag landing system for the spacecraft

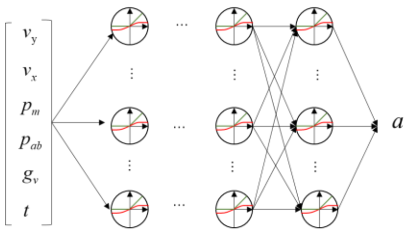

Figure 2: The architecture of multi-layer perceptron

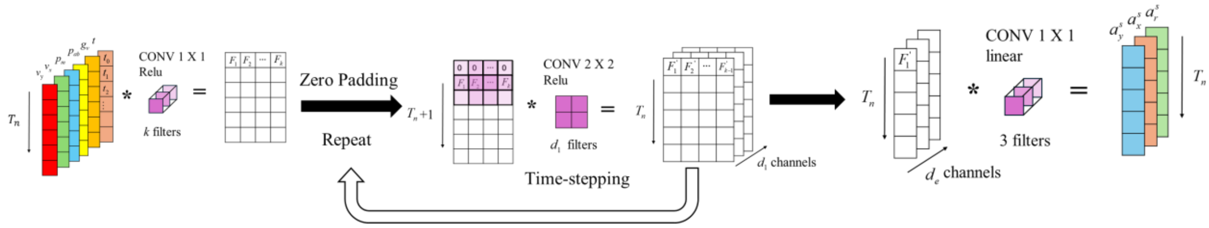

Figure 3: The convolutional neural network with time-stepping

To output all three types of impact response simultaneously in a more compact manner, we proposed another deep learning model under the framework of the convolutional neural network (Fig.3). 8 one-by-one convolution filters are used to form basic features. Each row of features contains information only for the current time step. Zero padding is then conducted only at the top of features, and 16 two-by-two convolution filters are applied to create higher-level features. The new features will contain the lower-level features and temporal information from the previous time step. Multiple filters are set to learn the different combinations of information in a time-stepping way. After repeating the operation of zero padding and two-by-two convolution, only one feature is formed in each channel. One-by-one convolution is then used again to create the final acceleration outputs. At the present work, we set 100 timesteps, which means learning one curve at a time. 99 complete curves were split into 90 training curves, 5 validation curves, and 4 testing curves. After training, the relative errors between the predicted and experimental values of the maximum localized y-axis acceleration are around 10%.

All models have good predictive performance in simulation time. By comparing predictions on longer time series, the CNN model demonstrates better extrapolation than the MLP model. The results indicate that deep learning models can improve the efficiency of system design optimization and real-time prediction.

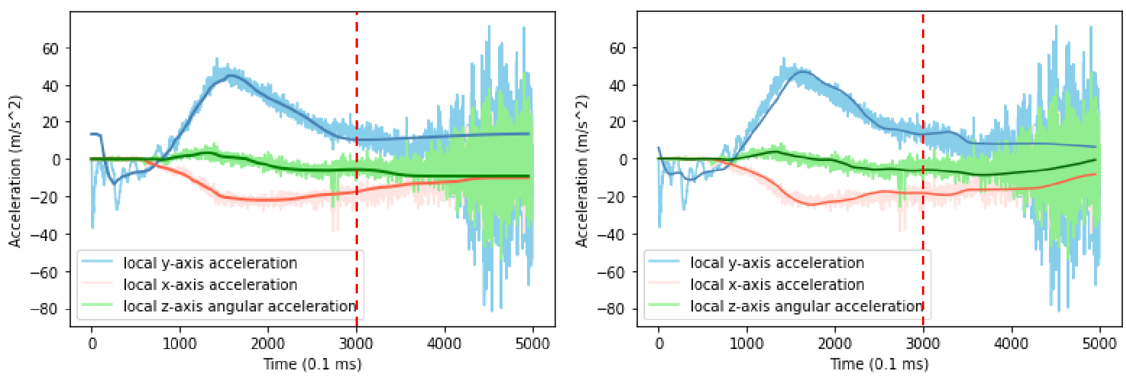

Figure 4: The comparison of extrapolation ability between MLP (left) and CNN models (right)

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