Stress-test a deep learning brain injury model using idealized impact kinematic profiles

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I. INTRODUCTION

Conventional finite element (FE) brain injury models require hours or even days on a high-end computer to simulate a single head impact. The rather poor efficiency poses a practical challenge for large-scale impact simulations or for offering prospective concussion risk assessment. Recently, deep learning brain injury models have been developed to dramatically reduce impact simulation runtime with sufficient accuracy in response compared to the directly simulated counterparts. For example, our group developed a convolutional neural network (CNN) that instantly estimates peak strains in specific brain regions [1] or elementwise peak strains of the whole brain [2]. Lately, the work has been further extended to using a transformer neural network (TNN) that instantly reproduces the complete spatiotemporal details of relative brain-skull displacement in a five-dimensional (5D) image format [3]. This allows efficient determination of voxelwise 5D strain tensor (over time, vs. peak values in earlier work). It has a high testing accuracy of normalized root mean squared error <2–3% and coefficient of determination, R^2>0.99, achieved at the time of peak displacement.

Nevertheless, deep learning models require thousands of training samples to be generated from conventional impact simulations. This demands an enormous amount of computing resources. Therefore, we explore whether the highly accurate TNN replica can be leveraged to efficiently produce training data with necessary and appropriate variations in impact kinematic features. This may provide insight into continual development of future deep learning models with an optimal set of training data (i.e. fewest number of impacts with well controlled profile variations) to achieve a desired accuracy. This study is the first step towards this goal, by stress-testing how the TNN performs using a set of idealized head impact profiles unseen by the training dataset.

II. METHODS

TNN was originally developed for natural language processing due to its improved ability (relative to other conventional architectures, such as CNN) in handling long range data. This turns out to be quite relevant to head impact simulation because brain deformation at the current time point depends on the entire history of loading conditions in terms of head rotational velocity/acceleration. Therefore, a TNN brain injury model was developed [3] and trained based on ~5 k head impacts augmented from real-world cases from the previous work [2]. All head impacts were simulated using the anisotropic Worcester Head Injury Model Version 1.0 (WHIM V1.0). The TNN was designed to predict relative brain-skull displacement in a 5D image format (3D voxels plus one dimension for the three displacement vectors and another dimension for time). This would approximately halve the output data size compared to predicting voxelwise strain tensors (6 unique tensor components due to symmetry vs. 3 displacement vectors). The image format also allows efficient computation of voxelwise 4D maximum principal strain (MPS) or the complete 5D strain tensor at voxel centroids [4].

To generate idealized head impacts, a haversine shape of rotational velocity profile was used. This shape of rotational profile ensured that the velocity itself and its acceleration profile, obtained from simple forward difference, would both start from zero and return to zero. This is expected to be physiologically plausible in real-world impacts. Ten head rotational profiles were generated so that they have random impulse duration (in the range of 20–50 ms, with an additional 20 ms of zero velocity and acceleration at the end), random rotational axis in space, and random peak rotational velocity magnitude (in the range of 2–40 rad/s). Random phase shift (within 20 ms) was also introduced among the three velocity components along the major anatomical axes. The profiles were then preprocessed according to the TNN input requirement. This included shifting the profiles so that the rotational velocity/acceleration started at 31 ms temporal location, padding of the profiles with zero velocity and

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acceleration so that the total length was 100 ms. Then, the corresponding rotational acceleration was scaled to 1% (to ensure comparable data range relative to rotational velocity). Finally, the rotational velocity and scaled rotational acceleration were concatenated into a 6-by-101 image format as input to the TNN. Voxelwise displacement vectors were then predicted using the TNN previously trained.

At the same time, the same head rotational velocity profiles were prescribed to the anisotropic WHIM V1.0 through the head centre of gravity for conventional impact simulation. The resulting elementwise brain-skull relative displacements were resampled to the same image format as from TNN (4 mm isotropic resolution and 1 ms temporal resolution). For both the TNN-estimated and directly simulated relative brain-skull displacements voxelwise strain tensors were computed [4], from which 4D MPS were obtained.

Performance of the TNN was assessed based on displacement and the resulting MPS, using coefficient of determination (R^2) and root mean squared error (RMSE). TNN required <1 s on a laptop to generate voxelwise displacement (and another 3-4 s for MPS) vs. ~30–60 min for conventional impact simulation.

III. RESULTS

The TNN remained highly accurate in predicting relative displacements for all the idealized profiles, even with the inclusion of relative phase shift among kinematic components. The resulting 4D MPS was also highly accurate. Figure 1 illustrates a typical idealized profile along with displacement and MPS on a coronal image plane between the direct simulation and TNN estimation. At the given time, the prediction had an R^2 and an RMSE of 0.999 and 0.0921 mm for displacement, and 0.996 and 0.007 for MPS.

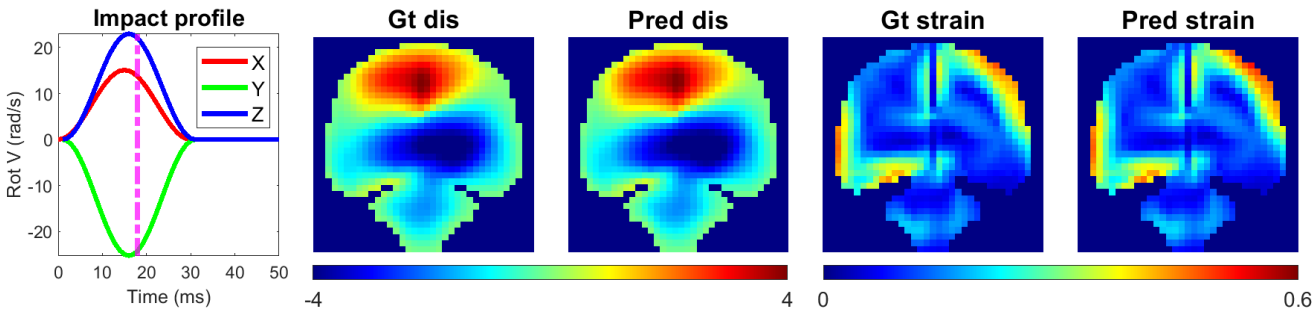

Fig. 1. An idealized impact profile and voxelwise displacement and MPS between direct simulation ("Gt") and TNN estimation ("Pred") at the time when peak displacement reached maximum. The TNN estimation remains accurate for profiles with another rotational axis, or even when relative phase shift is introduced among the three kinematic components.

IV. DISCUSSION

The shapes of idealized impact profiles can be easily controlled by a few well characterized parameters, such as impulse duration, peak velocity, rotational axis, and phase shift among the three components. This is otherwise challenging or infeasible at present for real-world impact data. In a relatively limited scope, this study confirms that the TNN remains highly effective in predicting the spatiotemporal deformation of brain in impact using idealized rotational profiles. This is the first step towards using the TNN replica to design an optimal idealized impact dataset for training a future deep learning brain model. In our next step, we will systematically introduce more variations in the idealized impact profiles or to parametrically generate more sophisticated kinematic profiles (e.g. with more kinematic peaks) to rapidly generate voxelwise displacement and strain. They will then serve as training data for a deep learning model based on a new or upgraded FE brain model (e.g. WHIM V2.1 or any other brain model). We will investigate the relationship between the number of idealized impacts and prediction accuracy from a deep learning model. This will help identify the fewest training samples necessary to achieve a desired accuracy, thus maximizing their effectiveness.

V. REFERENCES

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