Towards Efficient Brain Strain Estimation for Automotive Head Impacts via Transfer Learning

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I. INTRODUCTION

Computational head injury models are playing an increasingly important role in elucidating the biomechanical mechanisms of traumatic brain injury (TBI) for its ultimate detection, mitigation, and prevention. However, current head injury models require hours or even days on a high-performance computer to simulate a single head impact. They are too slow for any large-scale impact simulations or to offer any clinical concussion diagnostic capability in prospective applications.

Strategies to substantially increase model simulation efficiency typically involves various simplifications of the complex brain-skull dynamic system. For example, reduced order models simplify the head injury model into a mathematical equation [1][2]. A pre-computed brain response atlas simplifies head impact kinematic profiles into idealised shapes as model input [3]. More recently, a convolutional neural network (CNN) was also proposed [4] that learns the complex brain-skull dynamic response mapping without any simplification to the model or input. The technique instantly estimates peak maximum principal strain (MPS) in specific regions of the brain with sufficient accuracy. It was further extended to instantly estimate element-wise peak MPS of the whole brain [5] for impacts drawn from those in contact sports.

In this study, we extend the CNN technique to head impacts in automotive crashes. Compared to those in contact sports, head impacts in automotive crashes present further challenges—typically more complex head rotational velocity kinematics profiles with multiple peaks and much longer impact duration, i.e., up to 500 ms vs. typically 40–100 ms. Nevertheless, we investigated whether the pre-trained CNN based on the anisotropic Worcester Head Injury Model (WHIM V1.0) [6] and impacts in contact sports can be used to facilitate training for head impacts in automotive crashes using the Simulated Injury Monitor (SIMon) head injury model [7]. The latter head injury model was selected as it has been extensively used to simulate automotive head impacts.

II. METHODS

A total of 458 head impact kinematic profiles were obtained from two publicly available automotive crash databases, including 286 impacts from the National Highway Traffic Safety Administration (NHTSA) and 172 cases from the Insurance Institute for Highway Safety (IIHS). Each impact was simulated by SIMon using the corresponding ground-fixed rotational velocity profile as input. A typical impact of 200 ms required ~25 min to simulate on a high-end workstation (20 CPUs; Intel Xeon E5-2683 v4) using LS-DYNA (Version 971) and another ~20 min to obtain peak MPS of the whole brain over time, regardless of the location of occurrence.

The resulting impact-response samples served as a training dataset to train a baseline CNN with random weight initialisation. The previous CNN architecture [4] was further adjusted to accommodate the much longer temporal duration found in some head impacts, e.g., ~500 ms vs. 40–100 ms. Specifically, the kinematic input temporal length was adjusted from the previous 200 ms to 1000 ms, via replicated padding to maintain a zero acceleration, i.e., values at the two velocity profile borders were replicated along the temporal axis. The stride sizes of the first two convolutional layers were also increased from 1 x 2 to 1 x 4 accordingly (detailed in [4]).

The earlier pre-trained CNN using impacts in contact sports based on the anisotropic WHIM V1.0 [4] enabled transfer learning. Specifically, the converged weights from the pre-trained model served as the initial weights to train a separate CNN using the same earlier impact-strain training samples from automotive impacts and SIMon.

Performance was measured using repeated (N=5) 10-fold cross-validation by comparing the CNN-predicted

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MPS with the directly simulated responses in terms of coefficient of determination (R^2) and root mean squared error (RMSE). Performances of the two CNN models, with and without transfer learning, were compared. CNN required <0.1 sec on a laptop to estimate peak MPS of a head impact.

III. RESULTS

Without transfer learning, the CNN model only converged in 42% of the 50 trials tested. In contrast, 100% of CNN trials converged with transfer learning. Performances of the two CNN training scenarios were compared using only successfully converged trials. With transfer learning, the CNN achieved significantly higher R^2 and lower RMSE than the counterparts without (R^2 of 0.788 vs. 0.664 and RMSE of 0.045 vs. 0.056; p<0.01; Table 1). CNN-estimated MPS from a typical fold in a successful trial is further compared against the directly simulated, with and without transfer learning (Fig. 1).

TABLE I
PERFORMANCE COMPARISONS OF THE CNN MODELS BASED ON 10-FOLD CROSS VALIDATION REPEATED BY FIVE TIMES.

(N=458)	R^2	$RMSE$
With transfer learning	0.788±0.076	0.045±0.012
Without transfer learning	0.664±0.130	0.056±0.014

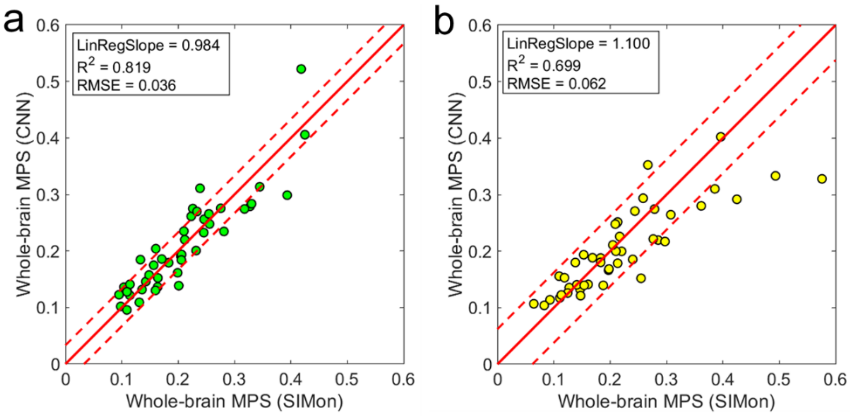

Fig. 1. CNN testing performances from one typical fold in a repeated 10-fold cross validation with (a) and without (b) transfer learning. Dashed lines: ±1 RMSE

IV. DISCUSSION

This study investigates how a recent convolutional neural network (CNN) technique developed for contact sports [4][5] can be extended to automotive head impacts. Instead of similarly generating a large amount of training samples (which is time consuming and resource demanding), we explore whether the previously trained CNN can be re-used to aid training with a different impact dataset and a different head injury model.

Our results indicate that transfer learning was indeed quite effective in facilitating CNN training (100% convergence rate vs. 42%). It also significantly improved the prediction accuracy (Table 1 and Fig. 1). These performance gains were obtained even though the pre-trained CNN was based on response samples from a different set of head impacts (contact sports vs. automotive crashes) and from a different head injury model (WHIM vs. SIMon). These findings suggest that the learned CNN neural network weights are capable of characterizing the underlying physics of head impacts, which is applicable to another head injury model or a different type of impact dataset. Therefore, transfer learning has the potential to significantly reduce the number of training samples required to achieve sufficient prediction accuracy for head impacts in automotive crashes.

V. REFERENCES

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