An Adaptive Transferring Framework to Accelerate the Development of Occupant Injury Prediction Algorithms

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I. INTRODUCTION

Automated vehicles are expected to improve road traffic safety through their advanced perception and decision-making capability, especially in imminent collision scenarios [1]. Meeting such expectations depends on accurate occupant injury prediction, which is usually established using data-driven approaches due to the inherent nonlinear characteristics of collision events [1-2]. In the concept design stage of a given vehicle model, large-scale crash data generated from numerical simulations become an essential data source for training injury prediction algorithms. Owing to the difference between vehicle models, occupant injuries can vary significantly even under the same collision conditions. Thus, engineers need to develop injury prediction algorithms by repeating the entire process (e.g. generating large-scale data, designing and training prediction algorithms) for each new vehicle model, which is highly time-consuming. Transfer learning (TL) is a machine-learning method that focuses on transferring knowledge learned from a previous task to a different but relevant task, which can promote learning efficiency [3]. Therefore, a well-designed TL method holds the potential to rapidly develop injury prediction algorithms for various vehicle models at a low cost.

II. METHODS

We proposed a vehicle-adaptive transfer learning (VATL) framework for ‘mapping’ injury prediction algorithms from one vehicle model to another (i.e. from sedan model A to B, Fig. 1(a)). Unlike traditional TL, VATL aims to adaptively identify the difference between various models and incorporate it into the training of injury prediction algorithms, which can effectively accelerate the development process without sacrificing prediction accuracy.

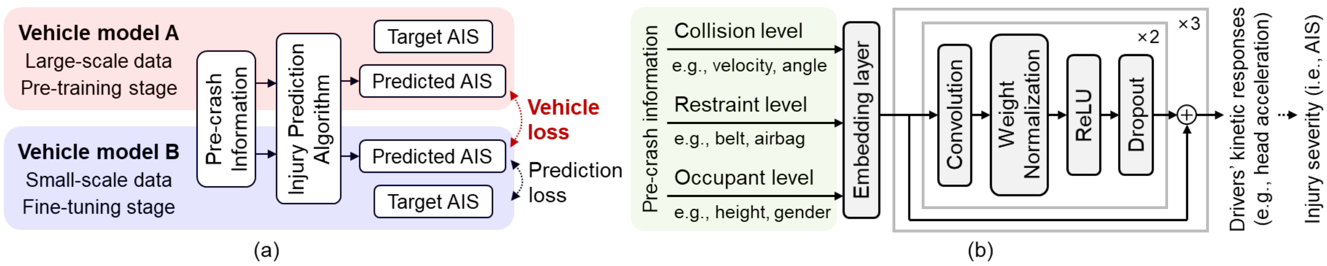

Fig. 1. (a) The proposed VATL framework. (b) Occupant injury prediction algorithms (taking TCN as an example).

Occupant Injury Prediction

For occupant injury prediction, the task is to predict occupants’ kinetic responses during a crash (then translated into injury severity, represented by AIS) from perceived pre-crash information (i.e. collision conditions, restraint configurations, and occupant characteristics). First, based on a large-scale crash dataset (5,000 cases for vehicle model A) [4], we trained three mainstream deep-learning algorithms, i.e. temporal convolution networks (TCN), long and short term memory (LSTM), and convolution-based LSTM (ConvLSTM) (Fig. 1(b)). The three algorithms are selected for comparison purposes in this preliminary investigation. Then, using VATL, we fine-tuned these algorithms on a small-scale dataset (500 cases for vehicle model B). The two sedan models are from different manufacturers and differ in both structure (middle-sized vs. compact) and restraint parameters.

Vehicle-adaptive Transfer Learning

Traditional TL methods directly fine-tune the pre-trained deep-learning algorithms on a new dataset without considering heterogeneity. But our experience on accident analysis confirms significant occupant protection differences between various vehicle models, even subject to comparable collision conditions. Therefore, it is necessary to quantify such heterogeneity between vehicle model A and B to help TL methods improve performance. For this purpose, except for the traditional prediction loss between the predicted AIS and target AIS, we used maximum mean discrepancy (MMD), a distance metric between two distributions on the probability

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space, to quantify the heterogeneity between vehicle models A and B (defined as 'vehicle loss' in our VATL framework, Fig. 1(a)). Specifically, MMD measured the difference in injury severity distributions between the two datasets. Guided by such vehicle loss, injury prediction algorithms can adaptively reduce such heterogeneity when transferring knowledge between the two tasks in the fine-tuning stage.

III. INITIAL FINDINGS

To fairly compare the performance of the proposed VATL framework, we introduced two baseline methods: (1) Non-TL (i.e. no fine-tuning by TL); and (2) TTL (i.e. fine-tuning by traditional TL without the vehicle loss). Taking head AIS prediction for example, as expected, VATL outperformed others regardless of the selected deep-learning algorithms and achieved a mean accuracy of 79.6% (Table I). The TCN algorithm with VTAL performed best and correctly predicted 83.6% of cases on a seven-category classification task (i.e. AIS: 0–6). Compared with TTL, training losses of VTAL decreased faster and converged steadily, reflecting a superior learning ability (Fig. 2(a)).

We further chose a typical case and analysed the prediction effect in detail to better compare and understand the three TL methods (Fig. 2(b)). Without fine-tuning, the predicted head acceleration curves by Non-TL deviated from targets, demonstrating that the injury prediction algorithm trained for one vehicle model is not feasible when it is directly applied to another vehicle. TTL improved compared to Non-TL by predicting the general trends of head acceleration. However, without the incorporated vehicle loss, the TTL method cannot adaptively quantify the heterogeneity between the two vehicles, resulting in prediction errors for head acceleration, especially in the curve peaks. In contrast, the predicted head acceleration curves by VATL were highly consistent with targets for all the deep-learning algorithms, demonstrating a satisfying and robust prediction ability.

TABLE I
ACCURACY FOR OCCUPANT HEAD AIS PREDICTION ON THE TEST SET [%]

	Non-TL	TTL	VATL
TCN	74.2	68.3	**83.6**
LSTM	12.0	77.2	78.0
Conv LSTM	70.2	67.2	77.2
Mean	52.1	70.9	**79.6**

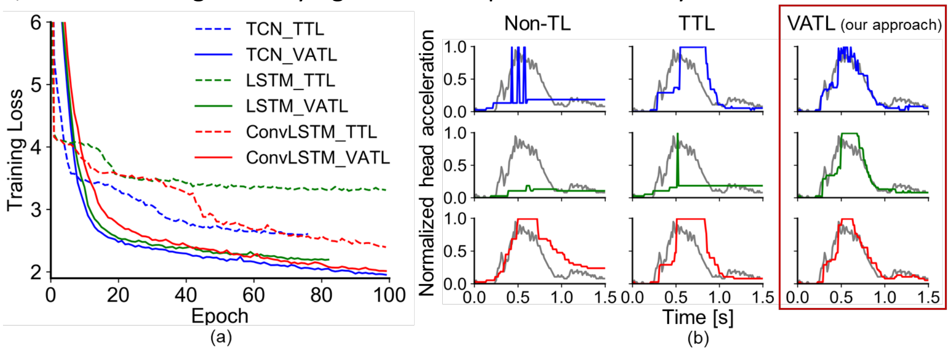

Fig. 2. (a) Training loss in the fine-tuning stage. (b) One typical head acceleration prediction case (grey lines: target curves, coloured lines: predicted curves).

IV. DISCUSSION

Expensive development costs render occupant injury prediction algorithms limited in practical application. To overcome this, the superior performance of TL methods in transferring knowledge can be harnessed to accelerate the development process. Specifically, we developed a VATL framework that can adaptively identify and quantify occupant responses in collisions between different vehicle models, which is tailored to develop injury prediction algorithms. The resultant acceleration manifests in the fast convergence of deep-learning algorithms (Fig. 2(a)) and less fine-turning data (500 vs. 5,000). It is estimated that the reduction in simulation cases can save about 1,350 h of computation time on a single computer (Intel i7-9700K 3.60GHz) [4]. The improved performance relies primarily on translating our experiences of occupant injuries into indicators that machine-learning tools can understand, e.g. defining 'vehicle loss' to quantify model heterogeneity as a preliminary attempt.

As a preliminary investigation, this study only validated the VATL framework between two sedan models (i.e. model A and model B). Further research efforts are necessary to assess its performance between more different models (e.g. sedans and SUVs) and its generalization ability to predict real-world accident injuries.

V. ACKNOWLEDGEMENTS

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VI. REFERENCES

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