A Framework for Near Real-Time Occupant Injury Risk Prediction using a Sequence-to-Sequence Deep Learning Approach

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I. INTRODUCTION

Accurate occupant injury risk prediction can largely benefit integrated safety systems and reduce fatality rates in motor vehicle crashes. This study proposes a framework of near real-time occupant injury risk prediction using a Sequence-to-Sequence (Seq2Seq) Deep Learning Model (DLM), where the entire occupant response 'sequence' is predicted using all available information in the vehicle deceleration 'sequence' (i.e. the crash pulse).

II. METHODS

For this initial proof-of-concept, we generated a large-scale computational database for training the Seq2Seq DLM, i.e. DLM Training Database (Fig. 1). The database used a Lumped Parameter Model (LPM) because of its capability for rapid preliminary evaluation of occupant injury risk levels [5-6]. We also generated a LPM Tuning Database comprising of hybrid Finite Element (FE) and Multi-Body (MB) model simulations for tuning the LPM parameters. Cases not used for training from both databases were used to validate the trained DLM.

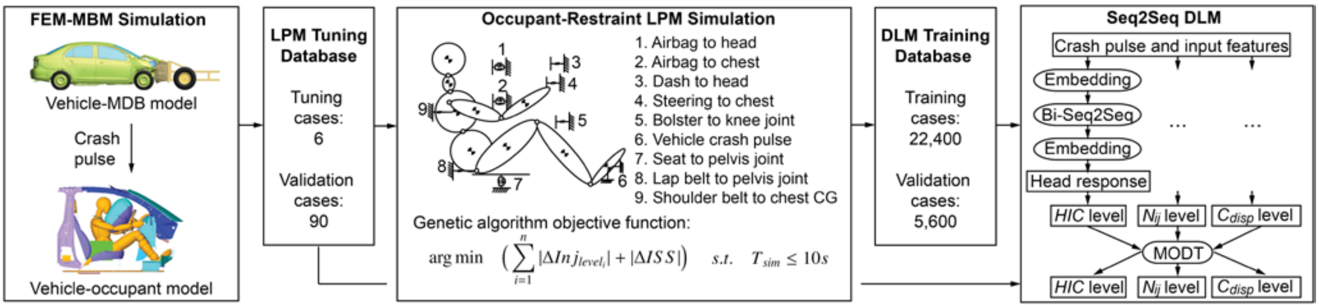

Fig. 1. Technical framework of the Seq2Seq DLM in predicting occupant injury risk.

LPM Tuning Database

A 96-case full-factorial simulation matrix was performed using the MADYMO solver and an existing hybrid FE-MB NCAC occupant-vehicle (Toyota Yaris 2007) model covering the following variables: (1) belt use (yes/no); (2) airbag use (yes/no); (3) occupant type (Hybrid III 5th%tile female and 50th%tile male); (4) delta-v (40, 50 and 60 km/h); (5) impact angle (-20°, -10°, 0° and 10°). For determining the input crash pulses, FMVSS 214 MDB collisions with the vehicle were simulated using LS-DYNA's FE solver [7]. The vehicle-MDB and occupant-vehicle model set-ups were validated with two crash tests available in the NHTSA database.

DLM Training Database

A frontal LPM was designed in MATLAB Simulink's Simscape, with particular focus on the occupant-restraint interactions in frontal and oblique MVCs (Fig. 1). The parameters were identified against six base cases of the LPM tuning database, such as belt w/o airbag, airbag w/o belt, etc., via genetic algorithm optimisation to minimise convergence time. The objective function used minimised the prediction error of the simulated occupant injury severity level with a constraint on simulation time. Thereafter, the LPM was validated with the remaining 90 cases by comparing occupant injury risk levels (Table I). Finally, a large-scale database of 28,000 cases representing frontal MVCs over a range of small oblique angles (-20° to 10°) with as input haversine crash pulses with varying peak amplitude (10–71 g) and duration (50–250 ms) was generated using the tuned LPM.

Seq2Seq DLM

The proposed deep learning architecture was implemented in TensorFlow and Python. The first four layers embedded the input crash pulse and three scalar features (belt use, airbag use and body size). This was passed

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on to a three-layer encoder-decoder Long Short-Term Memory (LSTM) Recurrent Neural Network (RNN) mechanism that models the conditional probability distribution for a hidden state vector representation [8]. The encoder was bi-directional to improve performance without causing forward-looking bias. The predicted kinetic response sequences of the occupant were used to determine the value of three injury indicators, i.e. Head Injury Criterion (HIC_{36}), Neck Injury predictor (N_{ij}) and Chest displacement (C_{disp}). Abbreviated Injury Score (AIS) injury levels were calculated with injury criteria and passed on to a Multiple Output Decision Tree (MODT) mechanism from Python's Scikit library to correct the prediction for structured output (i.e. multiple output prediction) [9]. This grid-search optimised DLM architecture also included regularisation, dropout and early stopping to prevent overfitting of the training data, i.e. preventing the model learning only the solution space. The trained DLM was validated by comparing predicted occupant response sequences and risk levels with the validation sets of the LPM Tuning Database (90 cases) and the DLM Training Database (5,600 cases).

III. INITIAL FINDINGS

The predicted occupant injury severity levels agreed well with the validation subset (Fig. 2). Near real-time performance was achieved with a single Seq2Seq prediction of an occupant's Injury Severity Score (ISS) taking 3.84 ±0.70 ms on an Intel i7-8550U 1.8GHz 26.43GFLOPS processor. The DLM proved capable of attaining a high number of correct predictions, with 83.6% of test set case ISS scores predicted correctly. N_{ij} prediction accuracy was slightly lower than other injury types. This is most likely due to the compounded prediction error originating from the three neck force sequences that must be predicted. The MODT was capable of accounting for multiple output prediction, evidenced by a 6.3% prediction accuracy increase for ISS.

TABLE I
MEAN INJURY INDICATOR PREDICTION ERROR OF THE LPM ON THE 90-CASE VALIDATION SET

Injury indicator	Prediction type	Mean prediction error
HIC_{36}		0.75 (±1.05)
C_{disp}	AIS (0–6)	0.17 (±0.68)
N_{ij}		1.34 (±1.69)
ISS	ISS (0–75)	7.31 (±12.0)

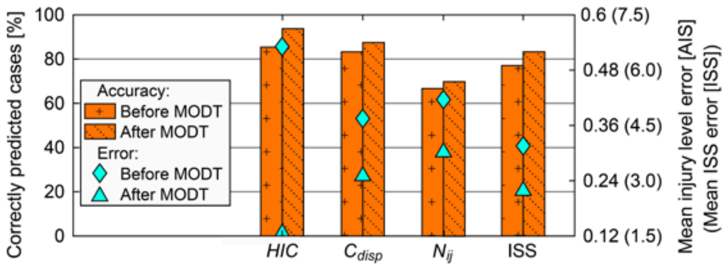

Fig. 2. DLM prediction accuracy on the validation sets from the two databases (5,690 cases in total).

IV. DISCUSSION

The present purpose-specific and task-optimised Seq2Seq DLM proved capable of near real-time prediction of the occupant injury risk levels with high accuracy and at low computational cost. Compared to conventional injury prediction algorithms (e.g. logistic regression), the advantages include computational efficiency, the exploration of all the available EDR information, the elimination of feature-engineering (i.e. processing and selection of input features) and the potential benefit in increased accuracy when increasing training data size [10]. At present, the algorithm is limited by the reliability of its validation data and the inability of current injury risk criteria to consider tissue level and internal injuries. As a preliminary investigation on the prediction feasibility of deep learning models in the safety field, further research efforts are necessary to fully validate this framework with a large-scale real-world or high-fidelity FE simulation database when it becomes available. It should also be further examined to what extent additional occupant and restraint information could be used to increase prediction accuracy.

V. ACKNOWLEDGEMENTS

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