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A framework to enhance FE-Human Body Models post processing

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1. Introduction

In human body models (HBM) finite-element (FE) simulations, robust and flexible post-processing is essential. Traditional methods based on local peak elements values or 95th percentile selection often lose information of spatial distribution and temporal evolution of injury, both crucial aspects for injury assessment.

Spatial distribution such as Clusters of Damaged Elements (CDE) offer insights that traditional methods cannot capture for example, in brain lesions or ribs fracture. Similarly, injury timing is critical, not only to account for interactions with the environment but also to evaluate injury progression. Time-based insights such as early rib fractures leading to worsened internal damage, or prolonged soft tissue strain can provide a more accurate assessment than conventional metrics.

Moreover, as biomechanics continues to evolve, there is a growing need for user-interactive tool that support both standard and custom injury criteria. This need is intensified by the use of a multi-scale approach combining local with global criteria, the high number of elements of HBMs and the volume of simulations.

To meet these challenges, we have developed a computational framework going beyond the application of predefined criteria.

2. Methods

The tool was developed using Python 3.11 with an object-oriented approach. It leverages the **lasso-dyna** library for LS-DYNA file reading.

2.1 Inputs

The framework starts with reading of LS-Dyna “d3plot” file. For analyses requiring high-frequency sampling the tool also supports binout binary files. The user can define parts and nodes of interest by providing their IDs. Custom injury criteria can be created based either on threshold or distributions of relevant metrics.

2.2 Data extraction and processing

Stress and strain tensors are extracted for all elements at each integration point. For each user-defined part of interest, element ids, types (solid, shell, beam) and nodes are automatically detected. With tensors, local metrics, such as Von Mises or maximum principal are computed for each integration point. Other quantities (for instance forces or nodal kinematic) are retrieved from “binout” file.

2.3 Analysis

Three hub impact simulations (frontal, lateral, and 60° oblique) were run using the THUMS AM50 v4.1 model for 50 ms, replicating the setup from **Kroell et al. (1971)**. The focus was on thoracic injuries, with criteria presented in **Table 1**.

A CDE detection was performed on ribcage to identify potential fracture sites. It relied on a density-based spatial clustering with at least 3 elements per cluster and a maximum distance between two neighbors of 10 mm. CDE detection allows automated counting and detection of failure sites. It can be applied with

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any static or time-dependent criteria. Each CDE point size reflects the number of elements involved. For illustration, results are shown at max. deflection and at the end of the simulation. Damaged elements were defined as those with an injury risk exceeding 50%.

Table 1. Regions of interest and injury criteria used.

Region	Injury criteria
Rib cortical bone	Maximum Principal Strain Probabilistic - Age 45 y.o **Larsson et al. 2021**
Costal cartilage	Maximum Shear Strain Probabilistic **Henak et al. 2017**
Whole thorax	Maximum resultant deflection (hub to T8)

3. Results and discussion

Fig. 1. presents the analysis results, showing variations in ribcage loading depending on the impact direction.

Current methods like threshold or 95th percentile can identify injured body parts but neglect spatial distribution, crucial for identifying rupture sites such as multiple rib fractures.

CDE detection addresses this issue by automatically revealing multiple injury sites on the same rib or cartilage which traditional methods would group into a single event.

This spatial information is particularly relevant for assessing thoracic injury severity. Indeed, both rib and cartilage failures are coded as rib fractures in the **Abbreviated Injury Scale** (**AIS**). They contribute to higher AIS and can lead to critical condition such a flail chest where three or more ribs are each fractured in at least two locations. This condition cannot be captured with traditional methods.

A slider enables time-interactivity, making possible exploration of injury evolution throughout the simulation.

Total size of simulations processed was 21 GB (7 GB x 3). For each, the processing time was 5s to read d3plot and 5s for ribcage analysis.

To summarize, the present framework features the following capabilities:

1. Computation of standard injury criteria
2. Easy implementation of user-defined metrics
3. Spatio-temporal injury visualization across body regions
4. Spatial clustering (CDE) over time to identify failure sites

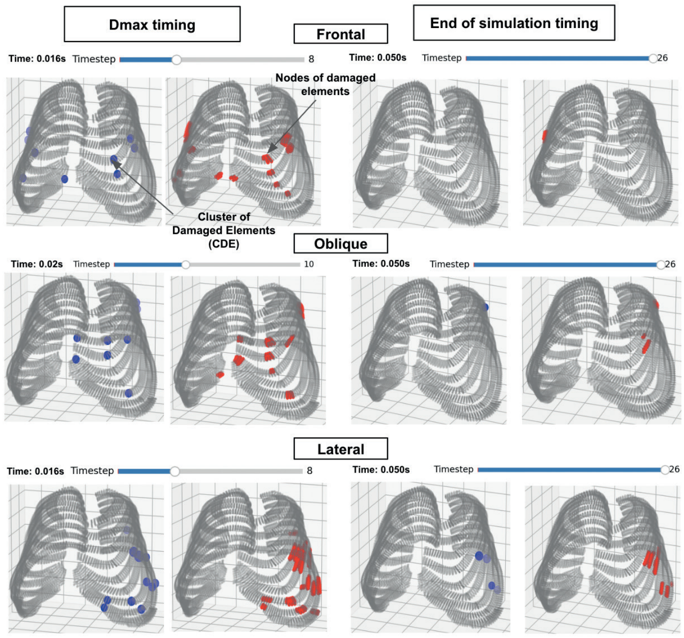

Figure 1. Rib cage (rib cortical bone and costal cartilage) injured elements clustering.

5. Automatization for multiple simulations
6. Compatibility with various HBM
7. Seconds computation time

These capabilities go beyond existing tools by enhancing injury assessment with spatio-temporal interactive analysis. Future developments will include more injury metrics, broader anatomical coverage, and improved compatibility with different solvers and HBMs.

4. Conclusions

The developed framework provides an automated, scalable solution for processing multiple simulations, extracting multi-scale injury criteria, and enhancing both analysis and visualization. By combining global and local metrics across body regions, it enables a more comprehensive injury risk assessment.

Conflict of Interest Statement

The authors declare that they have no conflicts of interest related to this study.

Contributor Roles

AG: Conceptualization, Methodology, Writing original draft, Writing-review & editing, Software; CBR: Supervision, Writing-review & editing PJA: Supervision, Writing-review & editing.

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