A Hybrid Risk Model for Hip Fracture Prediction Using Clinical and Stochastic Finite Element Data

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Introduction

There exist several hip fracture prediction model using clinical data. However, due to the complexity of hip fracture mechanism, the use of clinical data only might not be sufficient to ensure an accurate and robust hip fracture risk prediction model. In order to improve the risk model, the authors propose to supplement the clinical data with Finite Element (FE) data. The fusion of the two types of data is performed using a deterministic and a stochastic approach. The latter approach accounts for uncertainties in loading and material properties of the femur, which are propagated through the FE model.

Objectives

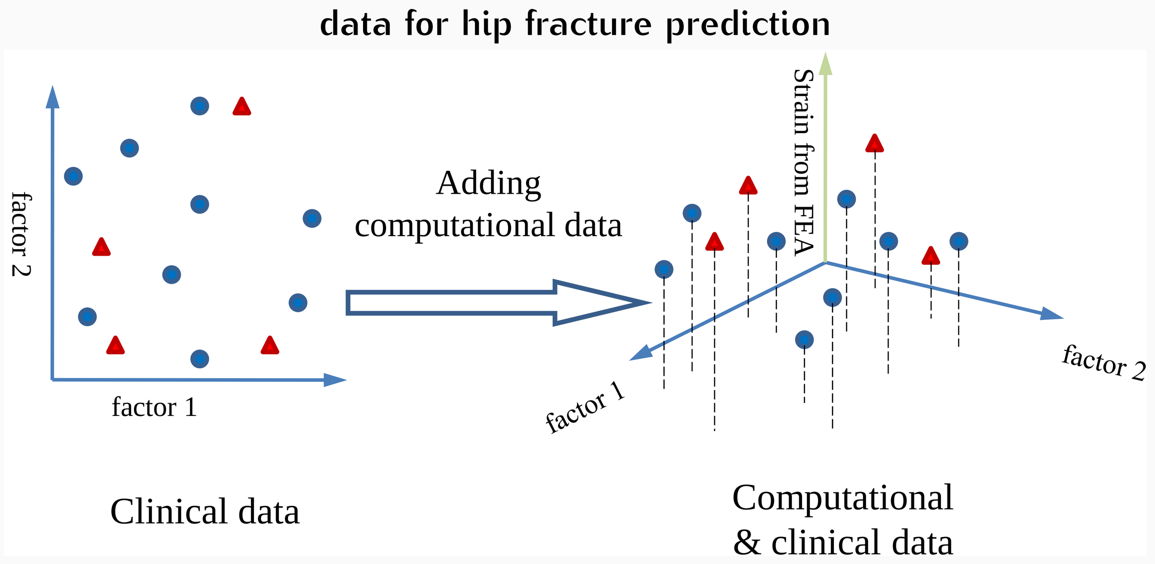
- Develop an SVM-based hybrid hip fracture risk prediction model by fusion of clinical and FE data.
- Propagate uncertainties through the FE model to make the computational content more realistic.

Methods

- Combining clinical and FE data for hip fracture prediction

One possible way of combining the data is to construct the prediction model in an "augmented space". Outputs of the computational simulations are used as additional input parameters for hip fracture prediction (Fig. 1).

Fig. 1: Combining clinical and computational data for hip fracture prediction



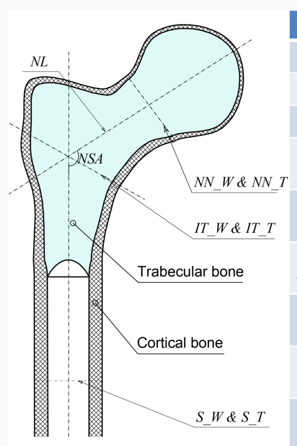
- Clinical data

The clinical dataset used in this study is a sub-cohort of the Women's Health Initiative (WHI). Besides conventional risk factors (lifestyle, family history, etc.), the database also includes hip geometric parameters (Fig. 2) extracted from patients' DXA images using Hip Structural Analysis.

Tab. 1: Conventional risk factors for hip fracture.

Parameter
Ethnicity
Self-reported health
Fracture on/after age 55
Physical activity
Smoking status
Parent broke bone
Corticosteroid use
Diabetes treatment
Age
Height
Weight
Hip total BMD

Fig. 2: Implemented parameters in the FE model.



Region	Parameter	Name
	Total weight	*WT*
Neck	Neck-shaft angle	*NSA*
	Neck length	*NL*
	Outer diameter of cortical bone	*NN_W*
	Thickness of cortical bone	*NN_T*
Inter-trochanter	Outer diameter of cortical bone	*IT_W*
	Thickness of cortical bone	*IT_T*
Shaft	Outer diameter of cortical bone	*S_W*
	Thickness of cortical bone	*S_T*

Methods - cont'd

- A fully parameterized FE model

Computational data are generated from a fully parameterized femur FE model, which can accommodate a wide range of hip geometry without relying on medical images. This model is validated using the clinical data.

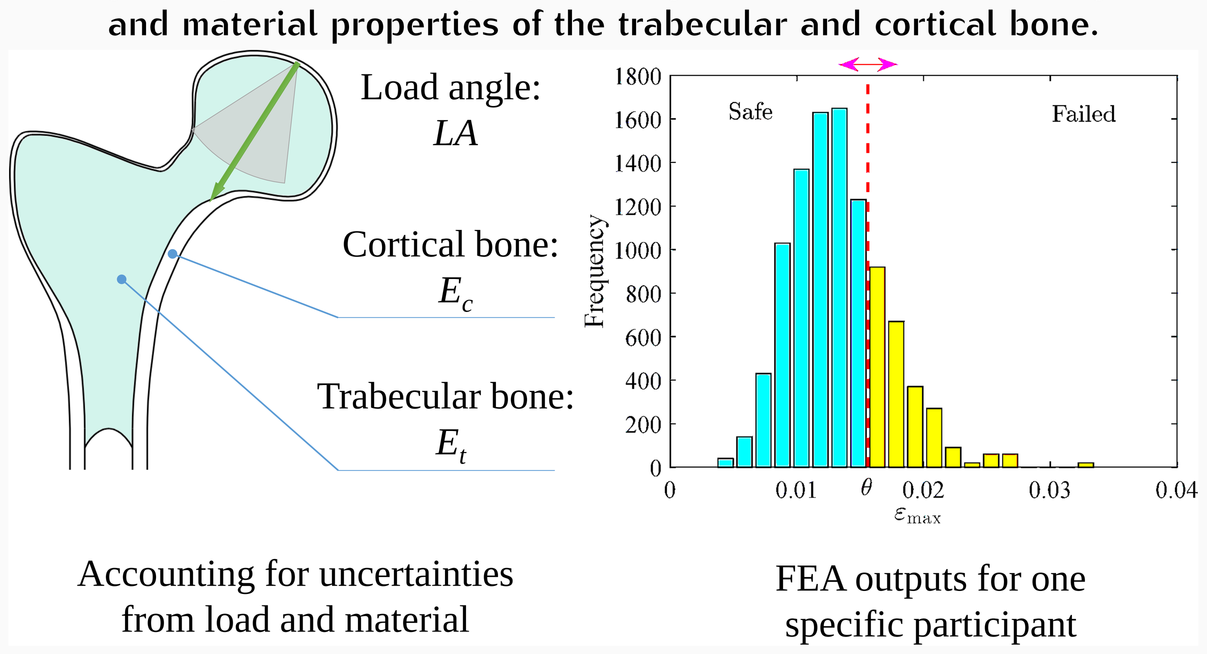
- Data fusion: Deterministic approach

This approach combines clinical and mechanical quantities from FE outputs (e.g., deteministic strain values ε_D) in the augmented space.

- Data fusion: Stochastic approach

The deterministic approach assumes that loads and bone material properties are exactly known, which is not realistic. The stochastic approach augments the clinical data using a stochastic quantity. The quantity is chosen as the probability (P_f) that ε_D is larger than a threshold. This probability is calculated using Monte Carlo simulation.

Fig. 3: P_f calculation by considering uncertainties in load angle and material properties of the trabecular and cortical bone.



→ Determination of the threshold θ

In this work, the threshold is chosen so as to maximize the predictive ability (area under the ROC curve (AUC)) of patient-specific P_f.

$$\theta^* = \arg\max_{\theta} AUC_{P_f}(\theta)$$

P_f that corresponds to the threshold θ^* is denoted as ε_S, which replaces ε_D and is added to clinical data.

Results

- Predictive ability of the FE model

Contour of maximum principal strain is provided in Fig. 4. If checked against the available clinical dataset, the FE model shows an AUC of 74%, which indicates a good predictive ability.

Fig. 4: Contour of computed maximum principal strain. The max is at femoral neck.

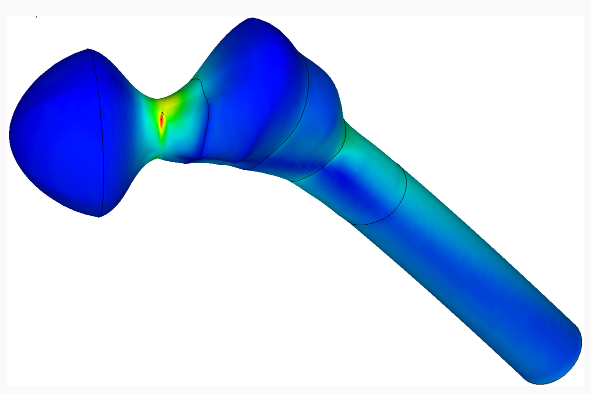
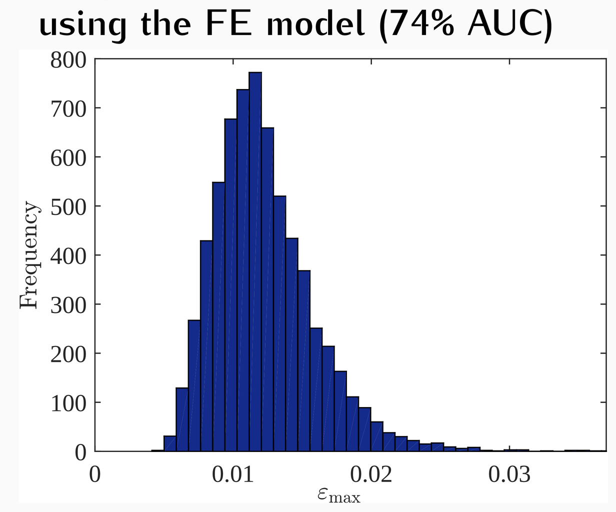


Fig. 5: Distribution of max principal strains of the WHI cohort using the FE model (74% AUC)



Results - cont'd

- Data fusion for hip fracture prediction

Tab. 2: Comparison of 10-year hip fracture prediction using deterministic and stochastic approaches.

Exp	Parameters	Validation dataset AUC	95% CI	ΔAUC
I	Geometric parameters + weight	0.77	[0.71, 0.83]	-
	Geometric parameters + weight + ε_D	0.81	[0.74, 0.87]	0.036
	Geometric parameters + weight + ε_S	0.83	[0.76, 0.89]	0.053
II	Conventional parameters w/o BMD	0.82	[0.74, 0.88]	-
	Conventional parameters w/o BMD + ε_D	0.83	[0.76, 0.89]	0.015
	Conventional parameters w/o BMD + ε_S	0.86	[0.80, 0.92]	0.045
III	Geometric + conventional w/o BMD	0.86	[0.79, 0.91]	-
	Geometric + conventional w/o BMD + ε_D	0.86	[0.79, 0.91]	0.001
	Geometric + conventional w/o BMD + ε_S	0.87	[0.81, 0.93]	0.015
IV	Geometric + conventional parameters	0.87	[0.81, 0.92]	-
	Geometric + conventional parameters + ε_D	0.87	[0.81, 0.92]	0.002
	Geometric + conventional parameters + ε_S	0.88	[0.83, 0.92]	0.013

→ The deterministic approach increases AUC by 3.6% and 1.5% in EXP I and II. No noticeable increase is observed for EXP III and IV.

→ The stochastic approach increases AUC by 5.3%, 4.5%, 1.5%, and 1.3% for EXP I through IV. The optimal strain threshold θ^* is 0.84%.

Conclusions

- A novel hybrid risk model for hip fracture prediction is consturcted by combining clinical and FE data.
- Both data fusion approaches tend to improve the predictive ability of the risk model and the stochastic approach exhibits larger improvement.

Future work

- Further investigation of data fusion schemes.
- Propagating other sources of uncertainties through FEA.

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