STRATIFYING HIP FRACTURE RISK IN THE FULL AGES REYKJAVIK COHORT USING FINITE ELEMENT MODELLING

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Introduction

Areal bone mineral density (aBMD) derived from DXA-scans has moderate accuracy in identifying subjects at-risk of sustaining incident hip fractures. Attempts have been made to overcome the limitations of screening with aBMD, by using femoral strength predicted from quantitative computed tomography (qCT)-based finite element models (FEMs) [1]. However, the results have been inconclusive with the predictive power of FEMs matching that of aBMD at best (incident fractures). This may in part be due to the limited number and sample size of FEM studies, whereas screening with aBMD has been validated against hundreds of thousands of datasets. One of the challenges, pertaining to building qCT-based FEMs, has been the manual labor associated with segmenting the qCT data. Recently, however, autonomous methods for segmentation have emerged.

The aim of this work was to predict the femoral strength for left and right femurs for all subjects in the AGES cohort, and to compare the predictive power of femoral strength to aBMD in terms of stratifying fracture risk.

Methods

Available for this study were 4799 CT datasets acquired at baseline in the AGES study as well as demographic data. Left and right proximal femurs were segmented from the images using our deep neural network-based approach [2]. The resulting masks were used to build 9598 FEMs in accordance with our previous work [3]. The models were loaded in a sideways fall configuration simulating impact at 1 m/s (**Fig. 1**). Here we report the results from 4560 out of 4799 left femurs that were available for analysis. The most common reason for exclusion was the presence of motion artifacts in the CT data. The operators working on the FEMs were blinded to hip fracture status (at 5-7 year follow-up) throughout the study.

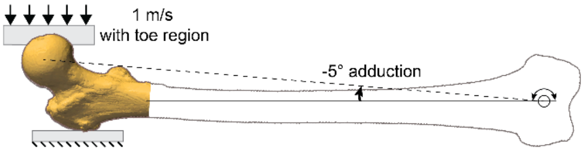

Figure 1: Boundary condition and loading conditions for the sideways fall simulations.

As DXA scans were not collected in AGES, CT-derived aBMD ($aBMD_{qCT}$) was used as a surrogate for DXA-derived aBMD ($aBMD_{DXA}$). Previous work [4] has established a relationship between the aBMDs as follows; $aBMD_{DXA} = 0.924*aBMD_{qCT} + 0.137$ (g/cm^2, R = 0.935). Predictive performance of femoral strength and $aBMD_{qCT}$ was evaluated using the area under the curves (AUCs) from Receiver Operating Characteristic (ROC) analysis. Boosting the predictive performance of $aBMD_{qCT}$ and femoral strength was attempted by adding variables reflecting functional status to regression models (time to walk 6 m, self-reported fall-frequency, isometric leg and hand strengths, and time-up-and go).

Results

Use of FEM-derived femoral strength resulted in higher AUC than achieved with $aBMD_{qCT}$ after adjusting for age and sex (0.794 vs. 0.769). Most functional parameters boosted the predictive performance of both femoral strength and $aBMD_{qCT}$ marginally. The largest boost was achieved with logistic models that incorporated age, sex, and time to walk 6 meters (0.801 for FEMs vs. 0.778 for $aBMD_{qCT}$).

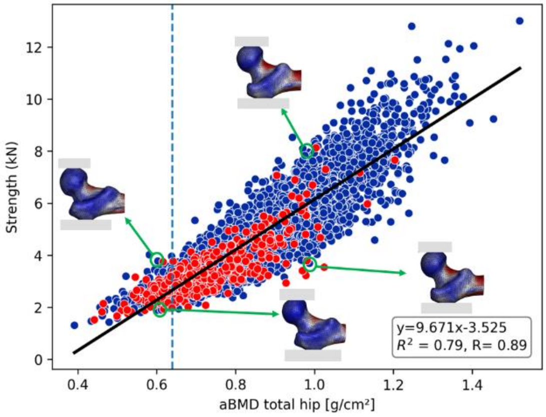

Figure 2: Femoral strength vs. $aBMD_{DXA}$ for 4560 subjects in the AGES cohort. Red circles indicate fracture cases and vertical line osteoporosis threshold.

Discussion

We found FEM-derived femoral strength to result in marginally higher AUC than $aBMD_{qCT}$ did in the AGES cohort. Functional biomarkers provided a small boost in performance for both $aBMD_{qCT}$ and femoral strength. We believe that this study demonstrates that image-based FEM technology has reached the stage where it is viable to carry out studies that are 1-2 orders of magnitude larger than current ones.

References

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Acknowledgements

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