Subject-specific Head Injury Models via Scaling Based on Head Morphology: Initial Finding

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Finite element (FE) models of the human head are important tools to study traumatic brain injury (TBI). However, most head injury models represent a population, rather than specific individuals. This could pose challenges in real-world applications due to significant individual variability. Although a method exists to generate subject-specific models *via* image registration and warping based on a generic model [1], it requires high-resolution anatomical neuroimages that typically do not exist for most subjects. While it is easy to measure head morphological features, scaling a generic model directly based on head size may not be sufficient to accurately match the brain. Nevertheless, head dimension has been shown to be statistically related to brain size [2]. In this study, we investigated the feasibility of scaling a generic head injury model based on the statistical relationships between head length, breadth and circumference that are most commonly measured [3] and brain morphological features to approximate individualised head injury models.

I. METHODS

We used the anisotropic version of the Worcester Head Injury Model (WHIM) [4] as the baseline to generate individualised models via scaling and morphing. First, the statistical relationships between head and brain morphology were determined from 192 subjects (142 males aged 14–25; 50 females aged 18–24; IRB approved). To ensure a consistent head orientation for measurement, the T1-weighted MRI used to create the WHIM was rotated so that its Frankfort plane was horizontal (baseline MRI), and the MRI of each subject was rigidly registered to it *via* an image-based algorithm. For each subject, head length (anterior-to-posterior), breadth (left-to-right) and circumference as well as brain length, breadth and volume were measured with existing approaches [3][5][6]. Using head length, breadth and circumference as well as gender and age as independent variables, a stepwise regression method [7] was used to fit three independent multivariate regression models to predict brain length, breadth/width, and volume. A Bayesian information criterion [7] was used for model selection.

To scale the generic model, scaling factors along three orthogonal directions were determined. With the regression models, the scaling factors for brain length and breadth (α_1 and α_2, respectively) were determined as the ratio of the predicted brain length/breadth with respect to their counterparts from the baseline MRI. For the scaling factor along the third inferior-superior direction (α_3), a dimensional analysis was used as brain volume was expected to be proportional to brain length, breadth and its third dimensional measurement, *brain height*:

$$\frac{v_b}{V_b} = \frac{l_b}{L_b} \times \frac{w_b}{W_b} \times \frac{h_b}{H_b}, \quad \alpha_1 = \frac{l_b}{L_b}, \ \ \alpha_2 = \frac{w_b}{W_b} \text{ , and } \alpha_3 = \frac{h_b}{H_b} = \frac{{v_b}/{V_b}}{{w_b}/{W_b} \times {l_b}/{L_b}}, \tag{1}$$

where l_b, w_b and v_b are the predicted brain length, breadth and volume from the regression models; L_b, W_b and V_b are the brain length, breadth and volume of the baseline MRI; and h_b and H_b are the hypothetical *brain height* from the subject and baseline MRI, respectively. A scaled model was then obtained by scaling the generic WHIM along the three orthogonal directions using the corresponding scaling factors.

For illustration, 11 subjects (from the smallest to the largest brain) were selected to generate scaled models. Their morphed models were created by non-rigidly warping MRI [1] (no landmarks necessary). To compare model simulation accuracy, a reconstructed National Football League head impact was used as input to the 11 pairs of head injury models for impact simulation (Case 84; peak linear/rotation acceleration of 82 g and 6228 rad/s^2 [8]). For each impact simulation, 95$^{\text{th}}$ maximum principal strains (ε) of the 50 deep white matter (WM) regions of interest (ROIs) and 54 cerebral grey matter (GM) ROIs were obtained based on their co-registered atlases [9-10].

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II. INITIAL FINDINGS

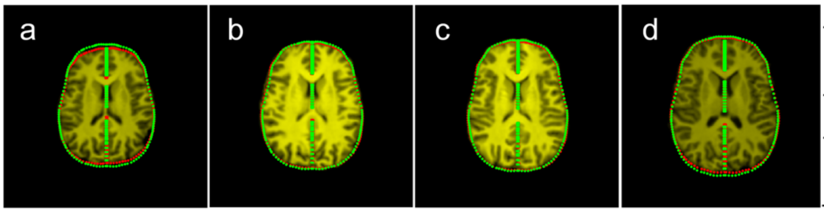
For illustration, the regression model for brain volume, v_b (in cm^3), is shown below with an adjusted R^2 of 0.63:

$$v_b = 72.86 \times len_{hd} + 67.67 \times breadth_{hd} - 45.69 \times gender - 6.80 \times age - 717.11, \quad (2)$$

where len_{hd}, $breadth_{hd}$, $gender$ and age are the subject head length, breadth (in cm), gender (0/1 for male/female) and age. Regression models for brain length (l_b) and width (w_b) were similar but are not shown (adjusted R^2 of 0.69 and 0.61 for brain length and breadth/width, respectively). All regression models were statistically significant (p<0.01).

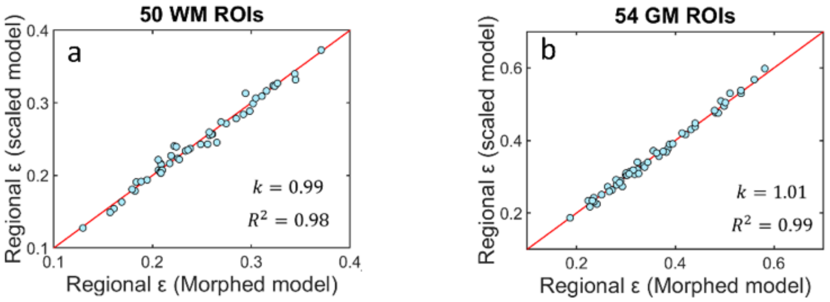
The scaling factors, α_1, α_2 and α_3, were 0.99±0.04 (0.92–1.05), 1.03±0.04 (0.95–1.07), 0.99±0.03 (0.93–1.03), respectively, for the 11 subjects. Fig. 1 compares the scaled and morphed models for four subjects. Linear regressions between the ε values of the 50 WM ROIs and those of the 54 GM ROIs from each pair of models were performed for each subject. The resulting regression slopes (k) were calculated, along with the coefficients of determination, R^2. The two models would generate identical responses when k and R^2 were both 1.0. Averaged from the 11 subjects, k was found to be 1.02±0.02, with R^2 of 0.97±0.01 for WM ROIs. They were 1.03±0.02 and 0.99±0.01 for k and R^2, respectively, for GM ROIs. Fig. 2 illustrates results for one subject.

Large differences could occur when comparing results from individualised models with respect to those from the baseline generic model, e.g., the regression slope, k, for the WM ROIs was 0.86 with R^2 of 0.93, and was 0.86 and 0.97 for GM ROIs, using the morphed model corresponding to the smallest brain as an extreme example.



Head	length(cm)	breadth(cm)	circumference(cm)
Range	17.7–21.6	13.8–16.2	50.6–61.2
Mean ± SD	20.1 ± 1.1	15.4 ± 0.8	57.0 ± 3.0
Brain	**length(cm)**	**width(cm)**	**volume(cm^3)**
Range	16.1–18.6	13.1–15.0	1223.2–2049.9
Mean ± SD	17.6 ± 0.7	14.1 ± 0.6	1662.9 ± 88.1

Fig. 1. Brain mesh outer boundaries overlaid on MRI for four subjects' scaled (green) and morphed (red) models (a to d; from smallest to largest brain). Right: summary of head and brain measurements of the 11 subjects.



WM ROIs	k	R^2
mean ± SD	1.02 ± 0.02	0.97 ± 0.01
GM ROIs	k	R^2
mean ± SD	1.03 ± 0.02	0.99 ± 0.01

Fig. 2. Linear regressions between ε values from the scaled and morphed models for the 50 WM ROIs (a) and 54 GM ROIs (b) for one representative subject. Summaries for the 11 subjects are on the right.

III. DISCUSSION

Individual variability of the human head/brain is an important factor to consider for real-world applications of head injury models. Based on a large set of neuroimages, we found that brain dimensions can be predicted using linear regression models based on head morphology, gender, and age. The regression models further allowed scaling a baseline generic model to approximate an individualised model using easily measurable head (but not brain) dimensions of the individual and measures of brain length/width/volume from the MRI of the generic model, without relying on individual high resolution neuroimages. The scaled models generated very similar responses with respect to the morphed models for each subject. However, large differences could occur when comparing responses from individualised models with those from the baseline generic model, indicating that individual variability should not be ignored. These results may provide a possible avenue for mitigating individual variations based on a generic model. Future study would assess whether including additional measures in the inferior-superior direction such as *chin-to-top* or *tragion-to-top* could further improve the regression models especially for brain volume.

IV. REFERENCES

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