Legal Majority Age Determination from MR Images of the Radius Bone

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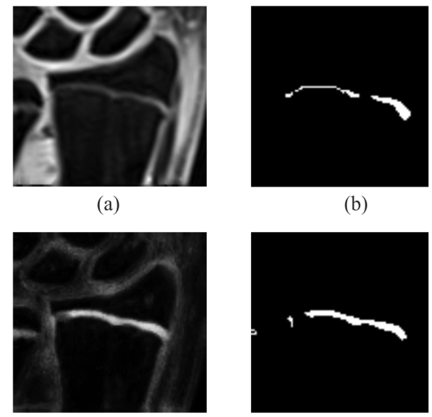
Target Audience: Forensic experts and radiologists interested in age estimation from MRI images.

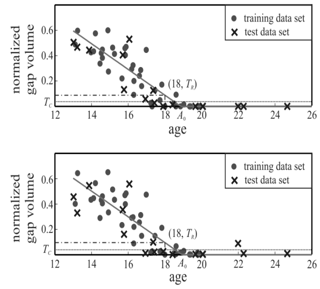
Purpose: An individual's legal majority age determination is a topic of growing interest in forensic practice. Victim identification, immigration hearings, and determining refugee status of asylum seekers underline the relevance of forensic age estimation (AE)[1]. Established AE methods use 2D X-rays, involving drawbacks due to projective imaging and radiation exposure. The use of MRI for AE enables an objective 3D assessment[2] without the legal implications of applying radiation in the absence of a medical or criminal indication. Standard methods based on the Greulich/Pyle or Tanner/Whitehouse atlas perform AE by subjective comparison of bone x-rays to reference images, leading to large inter-observer variability. A fully automatic software for 3D MRI age estimation would thus be beneficial to improve objectivity. A first step towards computer assisted age estimation from MRI images of the wrist is presented, by investigating the ossification of left hand radius bones (Figure 1a), which is the first bone a radiologist examines for AE.

Figure 1: (a) radius bone (b) manual segmentation of epiphyseal gap (c) probabilistic segmentation result of random forest classifier (d) segmented gap with proposed method.



Methods: A total of 60 T1 weighted 3D gradient echo (flash-vibe, water excitation, TR=14ms, TE=4.01ms, FA=15°) MR images of the left hand (acquired with a TimTrio 3T scanner, Siemens, Germany) were separated into a training (43) and a test set (17). The known ground truth age of the Caucasian male population has a mean of 17.1 years (SD 2.4, range 13.0 – 24.7). Images of the wrist had average volume and voxel sizes of 294x512x72 and 0.47x0.47x0.9 mm^3, respectively. Detection of the radius bone was performed manually by cropping the volume of interest. From a manual segmentation of the epiphyseal gap of the radius bone (Figure 1b), a classification algorithm based on the random forest framework[3] was trained, learning the location of the epiphyseal gap from the training data set. An automatic segmentation of the gap in unseen images is achieved by applying the learned classifier to test set (Figure 1c) and thresholding the results (Figure 1d). After computing the volume of the epiphyseal gap, linear functions were fitted to the training data volumes given their true chronological age (Figure 2). By evaluation on the test set, results for chronological AE were produced. From the linear functions a classification to determine legal maturity (below or above 18 years) was performed, by applying a threshold with equal sensitivity and specificity (T_C = 0.04).

Figure 2: Linear regression functions for age estimation (top: manual, bottom: automatic segmentation).



Results: Classification results for determination of legal maturity are shown in Table 1. An AE accuracy of 88.2 % for the manual segmentation and 76.5 % for the automatic segmentation was achieved. The mean difference of the estimated and the real age was 0.81 years. The uncertainty of the AE is shown in Figure 3 with box-whisker plots. Manual and automatic segmentation are shown separately such that the manual segmentation defines a baseline for the automatic results.

Discussion: Figure 2 suggests that the age of a person can be estimated based on the chronological age of the radius bone, due to a linear decrease of the volume of the epiphyseal gap for increasing chronological age. The best performance of the proposed method is indicated by the mean difference of estimated and real age for the manual segmentation and its value of 0.81 years is as expected, since the speed of bone aging varies between individuals[2]. AE accuracy and precision are slightly better compared to established methods using the Greulich/Pyle atlas, with a mean AE accuracy improvement of 0.4 years[4], while a comparison to the more time-consuming Tanner/Whitehouse method shows similar accuracy[4]. However, compared methods investigate all bones of the wrist, while the proposed technique currently focuses solely on the radius bone. The automatic method still shows room for improvement with an accuracy below 80% in determining legal majority age.

Conclusion: A method for AE from 3D wrist MR images was proposed, preventing the drawbacks of traditional X-ray based methods that involve harmful ionizing radiation. Automatic segmentation of the epiphyseal gap of the radius bone was investigated as a first step towards legal majority age determination from wrist MRI. The promising results indicate that the proposed method can be used, but further improvements in terms of accuracy are necessary for acceptance in forensic practice, e.g. by extending the method to more wrist bones.

References: [1] Bassed RB, Advances in forensic age estimation. *Forensic Sci Med Pathol*. 2012;8(2):194-6. [2] Dvorak J, et al. Age determination by magnetic resonance imaging of the wrist in adolescent male football players. *Br J Sports Med*. 2007;41(1):45-52. [3] Criminisi A, et al. Regression forests for efficient anatomy detection and localization in computed tomography scans. *Med Image Anal*. 2013. [4] Schmidt S, et al. Comparative analysis of the applicability of the skeletal age determination methods of Greulich-Pyle and Thiemann-Nitz for forensic age estimation in living subjects. *Int J Legal Med*. 2007;121(4):293-6.

Table 1: Classification outcomes (%) for legal majority age determination.

	TPR	FNR	TNR	FPR	ACC	PPV
manual seg train set	93.3	6.7	93.3	6.7	93.3	85.7
manual seg test set	80.0	20.0	100.0	0.0	88.2	77.8
automatic seg train set	91.5	8.5	91.5	8.5	91.5	80.0
automatic seg test set	70.0	30.0	85.7	14.3	76.5	66.7

Figure 3: Differences between AE and known chronological age for manual (GT) and automatic segmentation.