DETERMINATION OF LEGAL MAJORITY AGE FROM 3D MAGNETIC RESONANCE IMAGES OF THE RADIUS BONE

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ABSTRACT

The determination of an individual's legal majority age is becoming increasingly important in forensic practice. Established age estimation methods are based on 2D X-rays, but suffer from problems due to projective imaging and exposure to ionizing radiation, which, without proper medical or criminal indication, is ethically questionable and legally prohibited in many countries. We propose an automatic 3D method for the determination of legal maturity from MR images based on the ossification of the radius bone. Age estimation is performed by a linear regression model of the epiphyseal gap volume over the known ground truth age of training data. Results are comparable with the established Greulich/Pyle (GP) and Tanner/Whitehouse (TW) methods, but do not involve harmful radiation.

Index Terms **—** legal majority age, hand bones, bone age estimation (BAE), magnetic resonance (MR), segmentation, random forest

1. INTRODUCTION

Forensic age estimation of living individuals and human remains has become an important procedure in legal medicine. Example applications include victim identification after disasters or assessing living individuals entering a country without proper identification documents, when age status becomes important for criminal prosecutions, immigration hearings, and determining refugee status of asylum seekers [1]. Being based on ossification of the hand/wrist bones, bone age estimation (BAE) methods employ conventional medical imaging modalities to provide means for objective and reliable age estimation.

Different standards have been developed and are continually refined to make BAE applicable to many situations. The most widely used approaches in forensic practice for BAE are the methods proposed by Greulich/Pyle (GP) and by Tanner/Whitehouse (TW) [2]–[4]. Building upon the visual X-ray image comparison of the whole hand with a reference atlas, the GP method is fast and easy to use compared to the TW method, but shows larger inter-observer variability. Instead of using the hand as a whole, the TW method is based on comparing individual hand bones to reference illustrations using X-ray images. With the use of medical image analysis, different manual and automated methods have been proposed to make the evaluation procedure in X-ray images more objective and reliable [5], [6]. However, the examination of 2D X-ray images is limited due to the projective imaging configuration. Additionally, X-ray imaging involves an exposure to ionizing radiation, which is legally and ethically controversial when performed without medical indication, thus many countries prohibit its use for non-medical reasons.

Recently, magnetic resonance (MR) imaging has become an alternative in BAE research. It is not associated with harmful ionizing radiation and provides a detailed 3D representation of the anatomy. Further, MR imaging provides means for measuring bone and cartilage volume which may lead to improved reliability and precision. State of the art BAE methods using MR images are restricted to best-view cross sections to make use of estimation methods that were developed for 2D X-ray images [7].

The main goal of our research is to develop an automated method for determination of legal majority age based on BAE of all hand bones from MR images. This paper presents a first step in that direction, as we propose a method for determination of legal majority age based on an automated 3D segmentation of the gap between epiphysis and metaphysis of the radius bone. We focus on the radius bone, since its ossification is most clearly visible and is therefore the first bone examined by radiologists in BAE. The hypothesis is that the epiphyseal gap volume of the radius bone, which is segmented using a random classification forest from MR hand image training data, predicts the real age using a linear regression model. To determine whether a person is juvenile or adult, the linear regression model is used to define a binary classification into below and above 18 years, where the threshold in gap volume is derived from the training data.

2. MATERIALS

A total of 60 T1-weighted 3D gradient echo MR images of the left hand were separated into training (43) and test data sets (17). The known ground truth age of the Caucasian

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male population in this study has a mean of 17.1 years (standard deviation SD = 2.4 years, range of 13.0–24.7 years). Average volume and voxel sizes are 294x512x72 and 0.47x0.47x0.9 mm³, respectively. Since various methods for automatic detection of the radius bone in hand images can be found in the literature [9]-[10], the assumption is made that the radius bone was successfully detected and a volume of interest was appropriately cropped in a pre-processing step (see Fig. 1a). The ground truth segmentation of the gap voxels between epiphysis and metaphysis (see Fig. 1b) was created by a scientist well experienced in the analysis of 3D MR images.

3. AUTOMATED BONE AGE ESTIMATION

3.1. Segmentation of the epiphyseal gap in radius bone

Inspired by the work of Criminisi et al. [8] and Donner et al. [9], the segmentation of the gap between epiphysis and metaphysis in radius bone is based on a random classification forest (Fig. 1) that learns the gap location from the training data set. To decrease the computational effort for building the random forest, not all voxels in the training data set of radius bone images were used to train the classifier, but rather a smaller, specially selected set of voxels. For each tree, this voxel set is generated from the ground truth annotation of the gap and from the no-gap voxels which are selected based on the following probability:

$$p(x_n, y_n, z_n) = \frac{1}{3}\left(1 + |I(x_n, y_n, z_n)| + |G(x_n, y_n, z_n)|\right), \tag{1}$$

where $|I(x_n, y_n, z_n)|$ and $|G(x_n, y_n, z_n)|$ are the normalized image intensity and gradient magnitude of the n-th no-gap point in the radius bone images. The probability $p(x_n, y_n, z_n)$ favors the selection of soft tissue voxels surrounding the radius bone and edge voxels between radius bone and surrounding tissue. The random classification forest is therefore forced to learn from the image appearance of the surrounding soft tissue and the anatomical shape of the radius bone.

During training, classification trees are built by recursively selecting the best split between the gap and no-gap voxels that reach a specific node. For each node, the subset of feature vectors $f_j = (v_j, M_j)$, $j = 1,..,N_F$; and threshold values T_k, $k = 1,..,N_T$; are randomly generated, where $v_j = (x_j, y_j, z_j)$ is an offset vector in the 3D image coordinate system and M_j is an image feature selected as either image intensity or gradient magnitude. For each point i that reaches a node the following difference $d_{j,i}$ is calculated:

$$d_{j,i}(x_i, y_i, z_i) = M_j(x_i, y_i, z_i) - M_j(x_i + x_j, y_i + y_j, z_i + z_j). \tag{2}$$

Depending on the difference values $d_{j,i}$, each threshold T_k, splits the voxels that reach a node into two subclasses. The

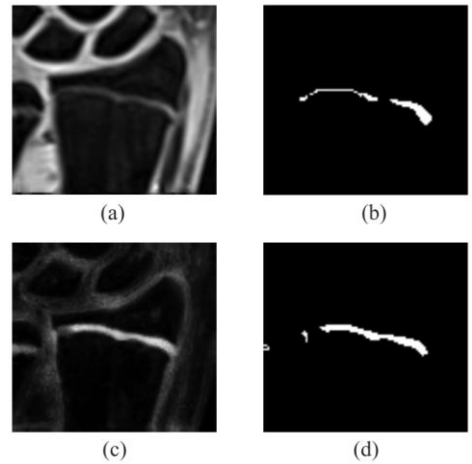

Figure 1. The gap between epiphysis and metaphysis in radius bone is segmented with a random classification forest in 3D MR images. a) The radius bone, b) manually segmented gap, c) obtained probability of the gap location from random forest and d) segmented gap with the proposed method. Illustrations correspond to the best-view cross section of the 3D MR image.

split that gives the highest information gain IG when separating gap and no-gap points, is selected as the best split and its feature vector f_B and threshold values T_B are stored in the node. The voxels of the subset where $d_{j,i} < T_B$ are classified to the left child node and the remaining voxels to the right one. The IG is given with the formula:

$$IG = \sum_{p \in \{L,R\}} \omega_p \cdot \sum_{q \in \{G,NG\}} p_{q|p} \log\left(p_{q|p}\right) \tag{3}$$

where $\omega_p = n_p/(n_L + n_R)$ is the ratio of the number of voxels classified to left (L) and right (R) child node, and $p_{q|p}$ is the probability that gap (G) or no-gap point (NG) is classified to left or right child node. When there is no improvement in the information gain or the depth of the tree reaches 15, the recursion stops with a leaf node. The count of the gap voxels which resemble gap probability are stored in the leaf. Since training data voxel subsets are randomly selected, and the feature vector and threshold are randomly generated, each tree in the random forest is therefore unique.

During testing, all image voxels of a test data set are routed from each tree root to a leaf by being pushed to the left or right child node depending on the feature vector and threshold value stored in the node. The gap probability stored in the reached leaf is accumulated at the location of the point in an image initialized in the same coordinate system as the observed 3D image of the radius bone (Fig. 1c). The values of the 3D accumulator normalized with the number of trees therefore represent the probability of the gap to exist at the respective location in the test image. The gap is segmented by thresholding the normalized 3D accumulator with the value T_P obtained for the minimal segmentation error in the training data set (Fig. 1d).

3.2. Determination of legal majority age

The chronological age of the radius bone is modeled as a linear decrease in the volume size of the gap between metaphysis and epiphysis with a regression function:

$$V = \begin{cases} k_1 \cdot age + k_2, & age < A_0 \\ 0, & age \geq A_0 \end{cases} \tag{4}$$

where *age* is the age of the person, V is the segmented gap volume that is normalized with the estimated weight of the radius bone, and A_0 is the age when the gap is no longer visible in the image. The coefficients k_1, k_2 and A_0 are determined by fitting the linear regression function to the segmented gap volumes using the training data set. The age of the person is therefore estimated solely based on the chronological age model derived from the radius bone. The legal majority age is determined by comparing the segmented gap volume with the value T_C that best separates the juveniles from adults in the training data set. The threshold value T_C corresponds to a binary classification with equal sensitivity and specificity.

4. EXPERIMENTAL SETUP

The number of trees $N_T = 25$ is obtained from the maximum curvature of the function representing the improvement in the segmentation precision according to the number of trees in the random forest. The depth of a tree $N_D = 15$ as well as the number of feature vectors $N_F = 50$ and threshold values $N_T = 25$ generated in each node was chosen as a compromise between segmentation performance and calculation time. To force the classifier to learn from the local anatomical structures, the maximal distance of the randomly generated offset vector is restricted to be $|v_j| \leq 40$ mm. The algorithm was implemented in MATLAB 64 on a Core i7 3.4GHz. Training time of the random forest was 3.5 hours and the testing time on average 45 minutes per image.

5. RESULTS

The proposed method for determination of a legal majority age was applied to T_1-weighted MR images of the left hand. Fig. 2 shows the chronological age model defined by the regression function (Eq. 4) obtained for the manual segmentation and proposed automatic 3D segmentation of the epiphyseal radius bone gap from the training data. The uncertainty in BAE, which was obtained as difference between the estimated and real age of the persons younger then $A_0 = 19$ (see Fig. 2), is presented in Figure 3 with box-and-whisker plots, where the estimations obtained from manual and proposed automatic 3D segmentation of the radius bone gap are shown separately for training and test data set. The results for determination of legal maturity based on the binary classifier with equal specificity and sensitivity ($T_C = 0.04$) are presented in Table 1, again separately for ground truth and proposed 3D segmentation.

Table 1. Classification results for determination of legal maturity based on the manual and proposed automatic 3D segmentation in the training and test data set. The classification outcomes are reported in percent (%) for equal specificity and sensitivity (TPR = TNR).

	TPR	FNR	TNR	FPR	ACC	PPV
GT training	93.3	6.7	93.3	6.7	93.3	85.7
GT test	80.0	20.0	100.0	0.0	88.2	77.8
3D seg training	91.5	8.5	91.5	8.5	91.5	80.0
3D seg test	70.0	30.0	85.7	14.3	76.5	66.7

* TPR, TNR, FPR, FNR are true positive, true negative, false positive and false negative ratio, respectively, ACC classification accuracy and PPV positive predicted value.

6. DISCUSSION

Up to our knowledge, the first method for automatic determination of legal maturity in 3D MR images was presented. A random classification forest was used to segment the gap between metaphysis and epiphysis in 3D MR images of the radius bone. Since the volume of the gap represents a small part of the radius bone volume, the use of all image voxels in building the random classification forest as proposed in [8] may not only require a long computation time and deep trees, but may also lead to overfitting to the no-gap voxels in the training data set. Each tree in the random forest is therefore trained on a small subset of image voxels that most distinctively represents the anatomical position and appearance of the gap and no-gap voxels. The image intensity and gradient magnitude are used to generate features that distinguish gap and no-gap voxels, we consider these two image modalities to contain sufficient information for successful classification. The long testing time can be explained by the fact that during testing each voxel of the image has to be classified according to the random forest, while during training of the random forest only small subsets of the voxels in the training data set were used. Figure 2 reveals that the age of a person can be estimated based on the chronological age of the radius bone, since the volume of the gap between metaphysis and epiphysis linearly decreases with age. The maximal accuracy of the proposed method is indicated by the mean difference of estimated age and real age for the manual segmentation and its value of 0.81 years is as expected, regarding the fact that the speed of bone aging varies between individuals [7]. Although the similar accuracy between the manual and proposed methods on the training data indicates that the method can be used in automatic segmentation of the radius gap in 3D MR images, the difference between training and test data for the proposed 3D segmentation is not negligible (Fig. 3). The difference may be due to the small training and test data sets, but may also be due to insufficient accuracy in the segmentation of the gap volume, especially in the final

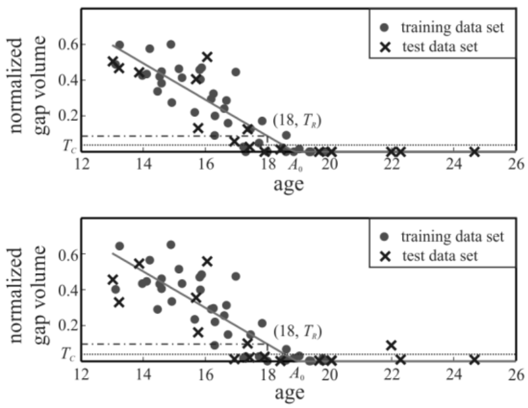

Figure 2. Bone age estimation model using a linear regression function of the radius bone gap volume between metaphysis and epiphysis over the known chronological age. Manual (top) and proposed automatic 3D segmentation (bottom), gap volume is normalized according to radius bone width.

stage of the ossification when the gap disappears from the radius bone. The volume of the gap between epiphysis and metaphysis linearly decreases with the age, and by the age of $A_0 = 19$ the gap is no longer visible in the radius bone (Fig. 2). The lower value of the classification threshold ($T_C = 0.04$) that best separates the juveniles from adults compared to the value of the regression function for the 18 years old person ($T_R = 0.09$) can be attributed to the precision of the method, but may also be due to the modest number of images in the testing data set. Compared with the results presented in the papers [4] and [10], the proposed method for the automatic determination of legal maturity in 3D MR images performs better than the GP method in both the mean BAE accuracy with an improvement of 0.4 years (Fig. 3) and in classification accuracy with an improvement of 8% (Table 1). The mean accuracy of the BAE is comparable with the 1.65 years obtained by TW method [4], while the accuracy of other methods that can be found in literature varies in the range from 0.36 up to 2.75 [2]. Nevertheless, all these methods are based on the visual estimation of all bones of the hand. The method that uses only radius and ulnar bones for the BAE in 2D X-ray images has shown an accuracy up to 3.2 years [11].

7. CONCLUSION

To conclude, compared to BAE methods established in forensic practice that are limited due to projective X-ray imaging and harmful exposure to ionizing, we proposed a method for determination of the legal majority age from 3D MR images, which is based on automatic 3D segmentation of the epiphyseal gap of solely the radius bone. Although the obtained results indicate that the proposed method can be used in the determination of the legal majority age, further improvements of the accuracy in the BAE are necessary to make the method acceptable in the forensic practice. Thus, further research will continue towards improving the 3D gap segmentation and extending the method to more hand bones.

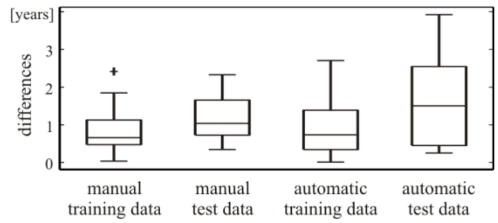

Figure 3. Distribution of the differences between BAE and known chronological age for the manual and proposed automatic 3D segmentation on training and test data sets.

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