# Learning-based Information Fusion for Fully Automatic MRI Age Estimation

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## Abstract

*Increasingly important for forensic medicine, radiological age estimation is performed by fusing independent bone age estimates from hand images. In this work, we investigate two fusion strategies of individual hand bone age distributions, and we show that the artificial separation into bone independent age estimates used in established fusion techniques, can be overcome. Thus, we treat aging as a global developmental process, by implicitly fusing developmental information from different bones in a dedicated regression algorithm. With* $0.82 \pm 0.56$ *years absolute deviation from chronological age on a database of 132 3D MR hand images, the results of this novel automatic algorithm are inline with radiologists performing visual examinations.*

## 1. Introduction

The estimation of an individuals age is an application of large interest in legal medicine and forensics. While the necessity of estimating unknown age of the deceased is e.g. required after natural catastrophes or mass fatality events like plane crashes, there has recently been a tremendous gain in interest in estimating the unknown age of living individuals [1], especially in the area of asylum seeking applicants. Due to a growing number of violent conflicts world-wide, more and more refugees enter Europe and the so-called Western world, which poses several challenges to the respective governments. One of these challenges is to determine if an asylum seeker is a minor, as to ensure the minors rights in the asylum seeking process. Since many asylum seekers lack valid identification documents, it has become a routine procedure to estimate unknown age by radiological age estimation procedures. The multi-factorial AGFAD guidelines [5] therefore suggest combining radiological determination of skeletal development, dental examination of the wisdom teeth and a physical examination.

A drawback of the established methods for age estimation is its subjectivity and reliance on out-dated reference systems. Thus, the radiological age estimation is based on a trained forensic radiologist visually comparing e.g. a whole hand X-ray image to a so-called atlas that describes typical age ranges of the developmental stages of a reference population. An example for such an atlas is widely used Greulich-Pyle (GP) system [3] for bone age estimation (BAE) based on the hand X-ray scans of adolescent volunteers enrolled in the Brush Foundation Growth Study from 1931 to 1942. To reduce observer-related subjectivity from the age evaluation, in Tanner-Whitehouse [7] (TW2) staging scheme ossification stage of epiphyseal growth plates of each hand bone is individually estimated. The subject age is then estimated by using a pre-defined nonlinear fusion function derived from characteristics of a sample population. Although, TW2 improves the inter- and intra-observers variability it is less common in forensic practice due to time consuming ossification stage estimation of each bone separately. Recently, reproducible automatic image analysis methods have appeared, most prominently BoneXpert [8], which imitates the atlas matching procedure of TW2 with an automatic hand bone segmentation and an extraction of image features describing ossification. By calibration to TW2, BoneXpert performs fusion of individual BAE based on the same pre-defined nonlinear function.

Another drawback of the established radiological age estimation procedure is its use of ionizing radiation to investigate ossification of epiphyseal growth plates in hand and clavicular bones as well as mineralization of wisdom teeth by a combination of X-ray and computed tomography (CT) scans. Many legal systems in Europe do not allow the application of ionizing radiation to healthy subjects, with Austria for example granting a legal exemption to allow this procedure in asylum seeking candidates. As a consequence, there has recently been a large interest in replacing the potentially risky radiological age estimation methods based on ionizing radiation with magnetic resonance imaging (MRI).

In our work, we develop and study fully automatic age estimation algorithms for non-ionizing MR images that

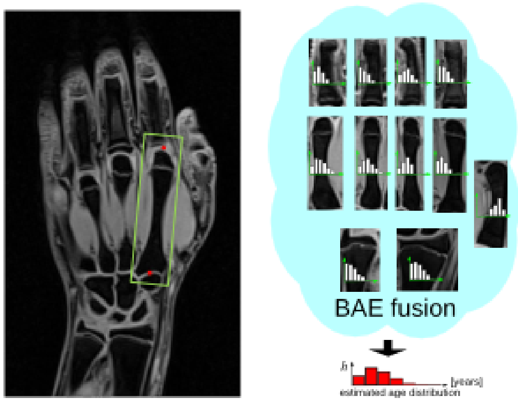


Figure 1. Fusion of the individual bone age distribution (right) from the automatically localized and cropped hand bones (left).

overcome previously mentioned drawbacks. Thus, we dedicated our work at the Ludwig Boltzmann Institute for Clinical Forensic Imaging on building an up-to-date 3D MRI data base of the age-relevant anatomical structures, i.e. hands, clavicle and wisdom teeth, acquired in a study involving male adolescent volunteers. Additionally, we focus our research on machine learning and computer vision techniques to both robustly localize e.g. the epiphyseal growth plates in hand bones [2] and to determine bone specific relationship of visual features in the images with the developmental phases of bone aging via nonlinear regression techniques [6]. In this paper, we propose two fusion approaches. In first approach, the nonlinear function that defines the contribution of individual BAE in the subject age estimation is learned via a meta-regression technique reflecting the fact that different bones finish ossification earlier than others. In second approach, a fusion function is learned simultaneously while extracting the aging features from the epiphyseal growth plates of each separate hand bones, thus the algorithm internally decides from which bones to learn the subjects age. While first approach differs from the TW2 as the nonlinear function is learned via the meta-regression technique, the second approach is more similar to the GP matching system by treating aging as a global developmental process, but in addition preserving estimation accuracy.

## 2. Method

Subject age estimation is built upon a Random Regression Forest (RRF) that automatically estimates age of individual hand bones from extracted aging specific features [6]. The method assumes hand bones have been automatically localized, aligned and cropped with an algorithm such as [2]. To estimate subjects age, a meta (MetaRF) fusion strategy based on learning the nonlinear regression function from the estimated age of individual bones is compared with an integrated fusion (IF) strategy that estimates the subject age directly from the aging specific features extracted from relevant bones according to the subjects age.

*RRF*: The nonlinear RRF can cope with arbitrarily large pools of randomly generated image features $f_i^b(\vec{x}; d)$ for computing trees of a forest during training the model. Thus, shrinkage and relevant feature selection for mapping ossification progress of individual bones $b$ to chronological age are performed implicitly in each tree node by maximizing information gain $IG$ over a random pool of features:

$$IG = |Var(S)| - \sum_{i \in \{L,R\}} \frac{|S_i|}{|S|} |Var(S_i)|. \quad (1)$$

Here $Var(\cdot)$ is the variance of age in a set of bone images, and $S$, $S_L$ and $S_R$ are the set of the bone images reaching the node and its left and right split subsets, respectively. The node splits are defined according to the binary test $f^b(\vec{x}_j; d_j) > \tau_k$, $j \in \{1..N_F\}$ and $k \in \{1..N_T\}$. At each node, feature parameters $(\vec{x}_j; d_j)$ and a threshold $\tau_k$ that best discriminates over the ages are stored. When the maximum tree depth $N_D$ is reached or there is no improvement in $IG$, the recursive splitting procedure is finished and histograms of the age distribution for the bone images that reach the leaf node are stored in the tree.

When testing a novel input image, feature responses are computed for test input $I_i^b$ based on the stored parameters $(\vec{x}_j; d_j)$, and the image is passed to the left or right child node according to the result of testing with $\tau_k$. The estimated bone age distribution $h^b$ is obtained by averaging the histograms from the reached leaf nodes of all RRF trees.

*MetaRF*: To investigate learning the nonlinear relationship between the development of individual bones, we create a meta Random Forest based on the bone age distributions $h^b$, splitting the available training data into two parts with a ratio $0.5$. A feature response $f_i(\xi; b)$ of the metaRF is a value at a randomly selected bin $\xi$ of the histogram $h^b$ of a randomly selected bone $b$. Based on these feature responses, metaRF is trained for each node by maximizing information gain according to Eq. 1 on the part of the training data reserved for learning the fusion of age distributions. During testing, we first apply the RRF method to the individual hand bones to obtain age distributions separately for each bone, and use these distributions as input for the metaRF, giving estimated subject age distributions $h_{mF}$.

*IF*: In the integrated fusion (IF) strategy, aging specific features are simultaneously selected from all hand bones, such that the algorithm internally decides which features from which bone are discriminative to estimate the subject age. Such an approach is well supported by the RF architecture as a simple feature parameter extension allows a selection of the bone in which the bone age regression is the most prominent. Thus, by making the bone number $b \in \{1, .., N_B\}$ a feature parameter $(\vec{x}; d; b)$, the features are generated from all hand bones at each node simultaneously and the parameters whose feature response produce

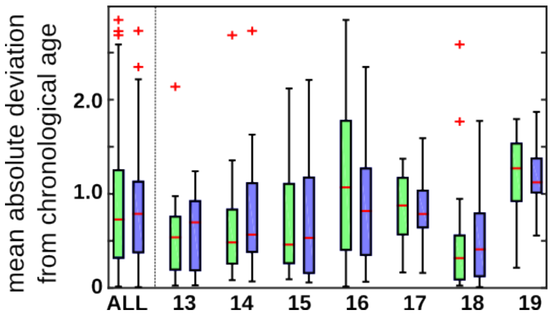

Figure 2. Age estimation results separately for each age group of the metaRF (left) and IF (right) fusion strategies.

the maximum $IG$ (see Eq. 1) are stored in the tree. At testing, the estimated subject age distribution $h_{IF}$ is obtained by using all bone volumes of a subject as input for the RRF.

*Experimental setup*: Our dataset of left hand T1-weighted 3D gradient echo MR images consists of scans from $N = 132$ male volunteers of known chronological age between 13 and 20 years, with in-plane resolution and slice thickness of 0.5 and 1mm, respectively. For evaluation, $N_B = 11$ bones are automatically cropped [2]. In RRF, $N_T = 1000$ trees of depth $N_D = 5$ were used and $N_F = 20$ features generated per node. Results of all experiments were computed in a leave-one-out cross-validation.

## 3. Results and Discussion

In this work, we investigated fusion strategies to automatically combine growth information from individual hand bones into an age estimate of a subject. Two promising fusion strategies capturing the highly nonlinear relationship between the development of individual bones were compared. Since individual hand bones follow ossification stages similarly, but with different timings, fixed rule fusion methods, e.g. mean, median or product of the BAE distributions, did not give satisfying results. By integrating prior knowledge on when metacarpals and phalanges finish ossification into the fixed rule fusion strategy as done in [6], an increase in estimation accuracy is also noted in our larger dataset of 132 subjects. Compared to our previous work [6], the herein proposed approaches are not dependable on accurate epiphyseal growth plate detection, whose inaccurate cropping might lead to unpredictable BAE results. Most accurate age estimation results are achieved with metaRF 0.85±0.64 and IF 0.82±0.56, represented as mean absolute deviations from chronological age ± its standard deviation. Detailed results of metaRF and IF are shown in Fig. 2. Age estimation results on our database of 132 MRI subjects obtained with both metaRF and IF approaches are comparable with the clinically established X-ray based methods, where deviations from 0.5 up to 2.0 years are reported [4]. To interpret these results note that the estimated age is the biological age of a subject, which might vary from the chronological age used in the comparison. To overcome this ambiguity, the automatic BoneXpert [8] method is calibrated by the same nonlinear function as used in the TW2 staging scheme and the reported results of 0.72 years on 1700 X-ray images (from 2 to 17 years) are obtained as deviation from the visual GP [3] atlas matching result. Besides the GP methods high intra- and inter-observer variability when used to estimate the ground truth biological age, the evaluation results of the BoneXpert [8] method also depend on the quality of the nonlinear fusion function. As the main goal of this work is to find the best fusion strategy, the nonlinear fusion function introduced by the TW2 method therefore cannot be used as the established ground truth bone age during evaluation. Our metaRF scheme calculates the nonlinear fusion of age estimates from individual bones and additionally the rater subjectivity from individual BAE is eliminated. To sum up, we have shown that our automatic IF strategy for fusion, which treats aging as a global developmental process, shows state-of-the-art age estimation accuracy without the artificial separation into individual bones.

## Acknowledgements

This work was supported by the Austrian Science Fund (FWF): P 28078-N33.

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