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Bone age cluster assessment and feature clustering analysis based on phalangeal image rough segmentation

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ABSTRACT

There are different feature selections in a bone age assessment (BAA) system for various stages of skeletal development. For example, diameters of epiphysis and metaphysis are used as sensitive factors during the early stage. Once the epiphyseal fusion has started, an additional feature such as the degree of fusion is extracted at the later stage. Image analysis is a critical point for feature selections to get a fine BAA, which includes ROI processing and feature extraction. Nevertheless, the related modeling techniques are various depending on the characteristics of different stages of bone maturity, which usually are taken as *a priori* knowledge in most previously proposed schemes. If a coarse bone age cluster (stage) for a hand radiograph could be automatically pre-assigned, then these corresponding image analysis methods can be identified. This could avoid taking *a priori* knowledge and provide a more flexible and reliable BAA system. For this purpose, a bone age cluster assessment system using fuzzy neural network (FNN) based on phalangeal image rough segmentation is presented in this work. This system includes two parts. The first part adjusts the feature weights to stable conditions according to four new defined bone age stages, which satisfy feature development of epiphysis and metaphysis. The second part is bone age cluster assessment on hand radiography based on the results of the first part. Experimental results reveal that the presented FNN system provides a very good ability to assign a hand radiograph to an appropriate bone age cluster and demonstrates the rationality of those new defined stages. Furthermore, the related feature clustering analysis for various stages is discussed to provide an accurate quantitative evaluation of specific features for the final BAA.

1. Introduction

Skeletal maturation estimation or bone age assessment (BAA) of children is a common procedure performed in pediatrics. Its object is to determine the skeletal maturation through a detailed examination of left-hand-wrist radiograph, which includes all relevant regions of interest (ROI). An incongruity between the bone age (developmental age of bones) and the chronological age (actual age at inspection time) indicates abnormalities in the skeletal development. This procedure is used in evaluating the growth disorder [1,2], monitoring the hormone therapy, and predicting adult height [3,4].

Generally, computer-assisted BAA (CABAA) system involves an image analysis of the ossification degree for carpal bones and epiphysis of tubular bones including distal, middle, and proximal phalanges based on Greulich and Pyle [5,6] and Tanner and Whitehouse (TW2, TW3) [3,4] methods. Following a classical learning scheme, these methods utilize automatic analysis of epiphyseal/metaphyseal regions of interest (EMROI) in a hand radiograph by first extracting a set of quantitative features sensitive to skeletal development and then creating a classifier according to these features (shown in Fig. 1). Depending on the changes in bony structures for phalangeal image, the epiphyseal/metaphyseal analysis is usually divided into two stages: the early and the later stage. Epiphysis changes in size fill up the gap between epiphysis and metaphysis at the early stage of skeletal development. Once the mature size is reached, both of them start to fuse from the middle and expand toward the edges at the later stage. This skeletal development is represented in Fig. 2.

Recently, a number of algorithms for CABAA focusing on the phalanges are proposed. Variety of features are extracted for different classifier in these approaches. Hsieh et al. [7,8] defined four ratios of epiphyseal shape as the geometric features to determine BA for all stages; they are edge/area, width/height, upper edge/width, and bottom edge/width. Aja-Fernandez's [9] method uses the relationships of epiphysis and metaphysis shapes such as presence, separation, diameter, and surface as the features for skeletal stage assigned.

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Various ROI processing and feature extraction methods for image analysis are employed to reflect the development stage due to the large difference of epiphyses shapes in each stage. For the early stage of development, regions of interest are subjected to an image segmentation procedure, which separates the epiphysis from the metaphysis. A wavelet analysis is used when the epiphyseal fusion starts [10]. As the development of epiphysis and metaphysis is not considered sufficiently under *a priori* age range constraint, the above-mentioned papers cannot do well for this issue.

Giordano et al.'s [11] method used three shape factors to compute the development stage of each bone for child between 1 and 12 years old. Pietka et al. [12–14] proposed a more refined approach to perform skeletal age assessment. In their approach, two classifiers are introduced for each EMROI: one, for younger children, uses the distance, shape and size features and another one, for older children, applies the wavelet features. When both stages of development interfere and all features are available, the outputs of both subsystems are averaged. No matter which kind of these two methods, the stage determination (either early or later stage) of each EMROI image must be taken as *a priori* knowledge for the classifier. So, the implementation of these classifiers is constrained by the selected features obtained from ROI processing. Moreover, only two bone age stages used are too cursory for the related selected features according to the analysis of actual development of epiphysis and metaphysis.

From the above observation it is suggested that the stage must be re-defined and a bone age cluster or stage for a hand radiograph must be automatically assigned before applying image processing procedure. Then the corresponding ROI processing and feature extraction methods employed for classifier could be identified to avoid taking *a priori* knowledge about the stage of each ROI development [11–14]. Therefore, a flexible and reliable classification can be provided to manage these ROI images from ambiguity. The presented improved CABAA system is shown in Fig. 3.

In what follows, a detailed description of the presented bone age cluster assessment scheme based on phalangeal image rough segmentation using fuzzy neural network (FNN) is given. This system includes two parts. The first part adjusts the feature weights to stable according to four defined bone age clusters, which satisfy feature development of epiphysis and metaphysis. A bone age cluster assessment on hand radiography is processed in the second part using the final feature weights obtained in the first part. Furthermore, a feature clustering analysis is presented to provide the identified image analysis method and the quantitative evaluation of specific features for final BAA.

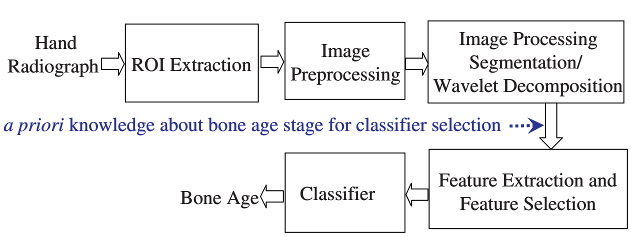

Fig. 1. Computer-assisted BAA (CABAA) system.

Experimental results show that the presented FNN system provides a very good ability to assign a hand radiograph to a suitable bone age cluster or stage and demonstrates the rationality of our new defined stages. Our dataset contains a total number of 600 normal child left-hand-wrist radiographs (0–14 years old) provided by Taichung Veterans General Hospital, where 40 radiographs per age group have been collected and nine EMROIs of the II, III, and IV phalanges are extracted from each radiograph.

2. Stage and feature analysis

Based on the Tanner and Whitehouse (TW2, TW3) [3,4] methods, the feature development of epiphysis and metaphysis could be applied to feature analysis for BAA. According to most previously proposed schemes [7–14], the related EMROI processing techniques are various depending on the characteristics of different stages of bone maturity, which usually are taken as *a priori* knowledge. These ROI processing methods such as segmentation and wavelet decomposition are applied to early and later stages, respectively. The results (as marked in Fig. 4) served as a basis for further feature extraction. All features are grouped into four sets according to the suggestion of Giordano et al. [11] and Pietka et al. [12–14] and illustrated in Table 1.

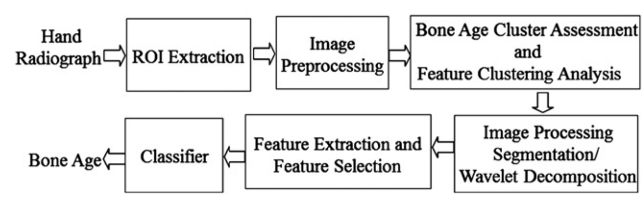

Fig. 3. The improved computer-assisted BAA (CABAA) system.

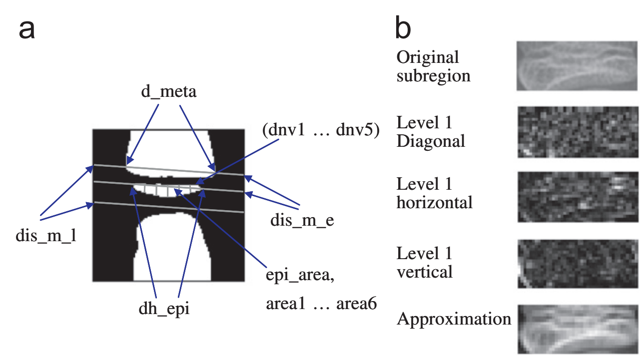

Fig. 4. The results of ROI processing using segmentation and wavelet decomposition: epiphyseal and metaphyseal diameters (dh_epi, d_meta), vertical diameters (dnv1…dnv5), distance between a metaphysis and diaphysis (dist_m_l), distance between a metaphysis and epiphysis (dist_m_e), epiphyseal area (epi_area), area of epiphyseal sectors (area1…area6). (a) The segmented EMROI. (b) Wavelet decomposition.

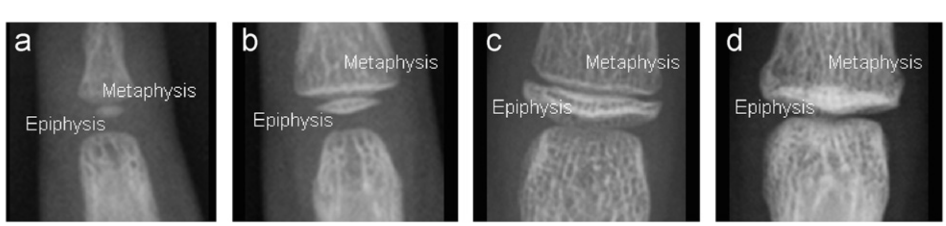

Fig. 2. (a–d) Epiphyseal/metaphyseal ROI at various stages of skeletal development.