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Automatic bone age assessment based on intelligent algorithms and comparison with TW3 method☆

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Abstract

Purpose: New algorithms are proposed to improve the validity, accuracy and practicality of automatic bone age assessment (ABAA).
Materials and methods: The concept of object-based region of interest (ROI) was proposed. Thirteen RUS (including radius, ulna and short finger bones) ROIs and seven carpal ROIs were appointed respectively according to Tanner–Whitehouse (TW3) method. Five features including size, morphologic features and fusional/adjacent stage of each ROI were extracted based on particle swarm optimization (PSO) and input into ANN classifiers. ANNs were built upon feed-forward multilayer networks and trained with back-propagation algorithm rules to process RUS and carpal features respectively. About 1046 digital left hand-wrist radiographs were randomly utilized half for training ANNs and the rest for ABAA after manual reading by TW3 method.
Results: BA comparison between observers indicated that the S.D. of RUS BA was larger than that of carpal BA (S.D. = 4.40, 2.42 respectively), but interestingly, both CVs were 4.0, and both concordance rates were very high (95.5% and 94.2%), and both differences between observers were not significant (both $P > 0.05$). We found by comparison between results of ABAA and manual readings that RUS BA had larger S.D.s than carpal BA between two methods, but the CVs were very similar in the case of carpal BA < 9 years and RUS BA ≥ 9 years (CV = 3.0, 3.1 respectively), apart from a comparatively larger CV for RUS BA < 9 years (CV = 3.5). Both parts of ABAA system, RUS and carpal, had very high concordance rates (97%, 93.8% and 96.5%) and no significant difference compared with manual method (all $P > 0.05$).
Conclusions: PSO method made image segmentation and feature extraction more valid and accurate, and the ANN models were sophisticated in processing image information. ABAA system based on intelligent algorithms had been successfully applied to all cases from 0 to 18 years of bone age.

Keywords: Computer-assisted diagnosis; Bone age assessment; Particle swarm optimization; Tanner–Whitehouse (TW3) method; Neural network model

1. Introduction

Bone age assessment (BAA), a common radiological examination to determine any discrepancy between skeletal age and chronological age, plays a vitally important role in diagnostic and therapeutic investigations of endocrinological and growth disorders in children, and quantitative assessment of skeletal maturity is also useful for predicting adult's height [1,2]. Two commonly used reference standards for BAA are Greulich–Pyle method [1] and Tanner–Whitehouse (TW3) method [2]. The former is an atlas-driven method and is based on visually comparing a nondominant hand-wrist radiograph with a number of atlas patterns. Bone age (BA) is assessed on the basis of the pattern, which most accurately resembles the clinical image according to the physicians' perception. The TW3 method uses a detailed shape analysis of several bones of interest, leading to their individual classification into one of several stages. Scores derived from stages of each interesting bone are summed to compute the assessment. Both methods are time-consuming, and experi-

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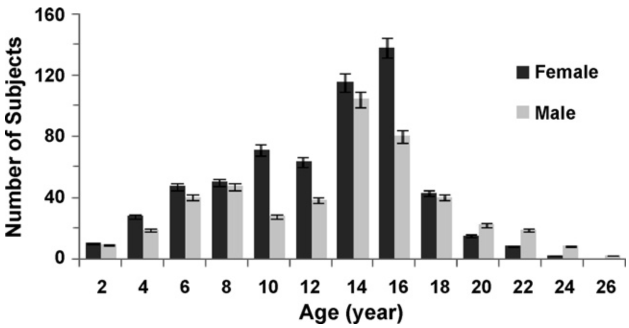

Fig. 1. Age and sex distribution of enrolled subjects.

enced pediatric endocrinologist or radiologist is needed to carry out the work.

The subjectivity of Greulich–Pyle method and the considerable complexity of TW3 method make the automatic bone age assessment (ABAA) a highly desirable goal to assist the radiologist or endocrinologist in performing a more objective, fast and accurate analysis without the intrinsic variability of human activities.

Several ABAA methods had been developed based on features extracted from region of interest (ROI) of hand-wrist radiographic image [3–5]. ROI segmentation and boundaries identification, however, are extremely challenging tasks, especially to carpal ROI. The appointed ROI is neither accurate nor objective. In addition, relevant knowledge rules used for bone age deduction and pattern recognition are hard to acquire and be expressed accurately. In order to surmount these drawbacks, two intelligent algorithms, particle swarm optimization (PSO) and artificial neural networks (ANN) were used in present study for fully automatic bone image segmentation, feature extraction and relevant knowledge processing.

2. Materials and methods

2.1. Dataset derivation and division

A collection of 1131 digital left hand-wrist radiographic images created from January 2006 to June 2007 was exported from the data bank of Department of Radiology, Tongji Hospital (Wuhan, China). Eighty-five (7.5%) photographs were excluded from the dataset for a variety of reasons such as malformed bones, bone age significantly exceeding 18 years, incorrect position of hands and wrists and incomplete images of fingers or wrists. Thus 1046 cases were enrolled. Subjects, aged from 3 months to 25 years of chronological age, mainly came from central China, who took X-ray photographs for growth and development evaluation. Distribution of age and sex of enrolled subjects see Fig. 1. Females accounted for 56.4% and right handedness 86.5%. Enrolled cases were divided randomly into two groups, half for training ANNs, and the rest for ABAA. All digital images were acquired with the Kodak Direct View DR 7100 system.

2.2. Atlas-driven method by operators

All 1046 photographs were read by two experienced pediatric endocrinologists. The appearance of 20 bones of a given radiograph was compared with TW3 atlas and the nearest match was selected. From these bones stages, two overall maturity scores are obtained, by summing up the 13 RUS scores and the 7 carpal scores respectively. Different ossification levels may appear pathologically or physiologically between RUS system and carpal system. As a result, carpal BA less than 9 years and RUS BA of all cases were assessed respectively.

2.3. Procedures for ABAA based on intelligent algorithms

The ABAA system was based on intelligent algorithms (Fig. 2). At data entry stage, ROIs were searched by PSO method. Numerical features of RUS and carpal were computed respectively from each image and stored in the database. In the meantime, manually assessed BA of RUS and carpal and other information of the same image were also input to the database. Then two ANNs, RUS ANN and carpal ANN, were trained separately by the referred features from the database and relevant knowledge was represented and obtained in networks. When input RUS or carpal features of query image most accurately matches that of certain BA in database, computer-assisted diagnosis (CAD) system then output the BA.

The ABAA system was accomplished under Windows Server 2003 on an x86-based machine (Intel Pentium D 945 CPU/1GB RAM). Moulds of feature extraction, PSO and ANN, were developed under Microsoft Visual Studio 2005 and the programming language is C++. Microsoft SQL databases, managed by Microsoft SQL Server 2005, were used to store images data and features data.

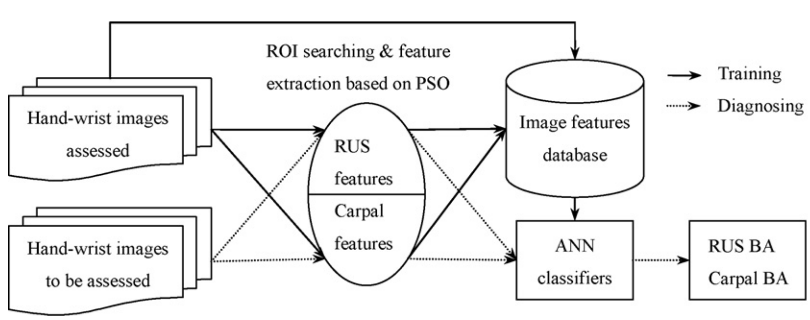

Fig. 2. Procedures of ABAA system based on intelligent algorithms.