Journal of Engineering Science and Technology Review 5 (1) (2012) 90 – 96

JOURNAL OF
Engineering Science and Technology Review

www.jestr.org

Review Article

Skeletal Bone Age Assessment – Research Directions

P.Thangam[1,] *, T.V.Mahendiran[2] and K. Thanushkodi[3]

[1]CSE Department, Sri Ramakrishna Engineering College, Coimbatore -641022, Tamilnadu, India.
[2]EEE Department, Coimbatore Institute of Engineering and Technology, Coimbatore - 641109, Tamilnadu, India.
Akshaya College of Engineering and Technology, Coimbatore -642109, Tamilnadu, India.

Received 7 August 2011; Revised 10 April 2011; Accepted 15 July 2012

Abstract

The work was motivated by the increasing awareness of the need for bone age assessment (BAA) schemes featuring an appropriate methodology for skeletal age estimation. The endocrinological problems in youngsters are already evident in many countries worldwide, varying in scale and intensity for different age groups and sexes. Change in lifestyles and eating habits of people also contribute to endocrine disorders, increasing the need for a system that predicts such problems well in advance. Skeletal bone age assessment is a procedure often used in the management and diagnosis of endocrine disorders. It also serves as an indication of the therapeutic effect of treatment. It is of much significance in pediatric medicine in the detection of hormonal growth or even genetic disorders. Bone age is assessed from the left-hand wrist radiograph and then compared with the chronological age. A discrepancy between the two indicates abnormalities. This paper consists of an overall review and technical assessments of various skeletal age assessment schemes in the literature. This review also recommends some research areas in this field and those leading to high efficiency are highlighted

Keywords: Bone Age Assessment (BAA), endocrine disorders, pediatric medicine, Skeletal Bone Age Assessment, left-hand wrist radiograph.

1. Introduction

The chronological situations of humans are described by certain indices such as height, dental age, and bone maturity. Of these, bone age measurement plays a significant role because of its reliability and practicability in diagnosing hereditary diseases and growth disorders. Bone age assessment using a hand radiograph is an important clinical tool in the area of pediatrics, especially in relation to endocrinological problems and growth disorders. A single reading of skeletal age informs the clinician of the relative maturity of a patient at a particular time in his or her life and integrated with other clinical finding, separates the normal from the relatively advanced or retarded [1]. The bone age of children is apparently influenced by gender, race, nutrition status, living environments and social resources, etc. Based on a radiological examination of skeletal development of the left-hand wrist, bone age is assessed and compared with the chronological age. A discrepancy between these two values indicates abnormalities in skeletal development. The procedure is often used in the management and diagnosis of endocrine disorders and also serves as an indication of the therapeutic effect of treatment. It indicates whether the growth of a patient is accelerating or decreasing, based on which the patient can be treated with growth hormones. BAA is universally used due to its simplicity, minimal radiation exposure, and the availability of multiple ossification centers for evaluation of maturity.

2. Background of BAA

The main clinical methods for skeletal bone age estimation are the Greulich & Pyle (GP) method and the Tanner & Whitehouse (TW) method. GP is an atlas matching method while TW is a score assigning method [2]. GP method is faster and easier to use than the TW method. Bull et. al. performed a large scale comparison of the GP and TW method and concluded that TW method is the more reproducible of the two and potentially more accurate [3]. In GP method, a left-hand wrist radiograph is compared with a series of radiographs grouped in the atlas according to age and sex. The atlas pattern which superficially appears to resemble the clinical image is selected. TW method uses a detailed analysis of each individual bone, assigning it to one of eight classes reflecting its developmental stage. This leads to the description of each bone in terms of scores. The sum of all scores assesses the bone age. This method yields the most reliable results. The high complexity of the TW method is the main reason for its less intensive use and what makes it worthwhile to automate. TW2 was a revision of TW1, especially in relation to the scores associated to each stage and also the difference between both sexes. In detail, in the TW2 method twenty regions of interest (ROIs) located in the main bones are considered for the bone age evaluation. Each ROI is divided into three parts: Epiphysis, Metaphysis and Diaphysis; it is possible to identify these different ossification centers in the phalanx proximity. The

* E-mail address: saithangam@gmail.com
ISSN: 1791-2377

development of each ROI is divided into discrete stages, and each stage is given a letter (A,B,C,D,…I), reflecting the development stage as: Stage A – absent, Stage B – single deposit of calcium, Stage C – center is distinct in appearance, Stage D – maximum diameter is half or more the width of metaphysic, Stage E – border of the epiphysis is concave, Stage F – epiphysis is as wide as metaphysic, Stage G – epiphysis caps the metaphysic, Stage H – fusion of epiphysis and metaphysis has begun, and Stage I – epiphyseal fusion completed. By adding the scores of all ROIs, an overall maturity score is obtained. This score is correlated with the bone age differently for males and females [4].

3. Developments of BAA systems

3.1 Fuzzy sets technique

The first attempts to achieve an automated system for BAA reported in the early 1980s. Pal and King proposed the theory of fuzzy sets and applied it for edge detection algorithm of X-ray images [5]. They used fuzzy functions along with the successive use of contrast intensifier to isolate the regions in the property plane, which could be used for further feature extraction from the X-ray films. They also proposed algorithms for automatic thresholding of grey levels using index of fuzziness and entropy of a fuzzy set.

3.2 Fuzzy grammar technique

Kwabwe et. al. later in 1986, proposed certain algorithms to recognize the bones in an X-ray image of the hand and wrist [6]. They used a shape description technique based on linear measurements from a polygonal approximation of the bones. The system was used to analyze age-related changes that take place with the growth in the bones. A fuzzy classifier for syntactic recognition of different stages of maturity of bones from X-rays of hand and wrist using fuzzy grammar and fuzzy primitives was developed by Pathak and Pal [7]. It comprised of a hierarchical three-stage syntactic recognition algorithm, which made use of six-tuple fuzzy and seven-tuple fractionally fuzzy grammars to identify the different stages of maturity of bones from X-rays.

3.3 Model-based technique

Michael and Nelson [8] developed a model-based system for automatic segmentation of bones from digital hand radiographs named as HANDX, in 1989. This computer vision system, offered a solution to automatically find, isolate and measure bones from digital X-rays. The preprocessing stage separates background regions from the tissue and bone regions using model parameters and model-based histogram modification. The segmentation stage finds the outlines of specific bones in the image using slice representation and binary overlay. A particular bone is found by obtaining a few boundary points, isolating the bone using an adaptive contour-follower called butterfly. The measurement stage obtains width and length measurements relative to the axis of least inertia of the filled-in bone outline. Though the HANDX system was robust and fast, it required extensions such as more a priori information to be incorporated into the model and include additional segmentation schemes such as a region growing scheme.

3.4 Phalangeal analysis technique

In 1991, Pietka et. al. described a method [9] based on independent analysis of the phalangeal regions. First an upright PA view of the left hand image was obtained. Then the phalangeal analysis was performed in several stages. The first stage standardized the image by removing the unexposed background and rotating the remaining part to achieve a normalized position of the hand. Then the phalangeal region of interest (PROI) was identified which included the phalanges and epiphyses. Then two vertical lines were scanned in the central part of the PROI and moved in opposite directions towards the periphery until the last pixel within the hand was found. This defined the left and right borders. The entire PROI contained the phalanges, epiphyses and parts of metacarpals. Then the Sobel gradient image was created, which was then thresholded using an empirically determined value to find the edges of both bones and epiphyses. The measurements were converted into skeletal age by using the standard phalangeal length table proposed by Garn et.al [10].

3.5 CACAS system

Tanner and Gibbons introduced the Computer- Assisted Skeletal Age Scores (CASAS) system in 1992 [11]. This was based on nine prototype images for each bone, representing the nine stages of maturity. Thus, a stage was defined by an image template. The input radiograph was manually zoomed in on each bone with a video camera and the bone was matched with two or three most similar templates. The system then automatically computed a measure of correlation to each template and a fractional stage. The correlation to the template was a measure of similarity. The CACAS system was seriously considered by the pediatric community as a move in the right direction. The rater variability was greatly reduced, thus enforcing consistency and also exhibited continuity.

3.6 Dynamic Thresholding technique

In 1993, Pietka et. al. performed phalangeal and carpal bone analysis with image processing techniques using digital radiographs to assess skeletal age. Initially the unexposed background is removed, the average gray scale value is calculated, using which the image is thresholded, from which the hand orientation to upright, PA view is determined. Analyzing the shape of the hand in the thresholded image, the carpal bone region of interest (CROI) is located. The CROI was defined using a standard threholding technique to separate the hand from the background. Then a dynamic threholding method was used with variable window sizes to differentiate between the bones and the soft tissue. Then mathematical morphology was used to remove the bones intersecting the borders of CROI such as radius, ulna and metacarpals. Then the objects included in the corrected CROI were separated and described in terms of features. A two dimensional feature selection analysis was used to compare the discriminant power of the features for BAA. For each carpal bone, eight features were considered. Feature selection removed the features of low discriminant power and reduces space dimensions. From the selected carpal bone parameters, the skeletal age could be estimated by further analysis. This system demonstrated the importance of using a multidimensional feature analysis for BAA. It also showed that area, perimeter, ratio and number of carpal bones were the most important features to be considered. These parameters together with the parameters extracted from the phalangeal analysis could be used to assess the bone ages.

3.7 Region based technique
Manos et. al. developed computer based techniques, in 1994 for the segmentation of hand-wrist radiographs and in particular those obtained for the TW2 method of skeletal bone age assessment [13]. The segmentation method was based on the concept of regions and consisted of region growing and region merging stages. Then in the bone extraction stage, the regions were labeled either as bone or background using heuristic rules based on grey level properties of the scene. Finally conjugated bones were identified by segmenting the bone outlines. The segmented regions could be further used as ROIs in BAA using the TW2 method.

3.8 Texture Information Technique
Cheng et. al. [14] proposed the methods to extract a region of interest (ROI) for texture analysis in 1994, with particular attention to patients with hyperparathyroidism. The techniques included multiresolution sensing, automatic adaptive thresholding, detection of orientation angle, and projection taken perpendicular to the line of least second moment. Texture information was collected in the form of a concurrence matrix within the ROI. The study was a prelude to evaluating the correlation between classification based on texture analysis and diagnosis made by experienced radiologists.

3.9 Fourier analysis Technique
In the same year, Drayer and Cox [15] designed a computer aided system to estimate bone age based on Fourier analysis on radiographs to produce TW2 standards for radius, ulna and short finger bones. It employed template matching of each bone to the scanned image of the radiograph. The computer generated a stage of bone maturity, individual and total bone scores and a value for bone age. The bone ages assessed by the computer-aided system were no different from the original TW2 reference values. The system was used to assess the bone ages of tall Dutch girls and the results obtained were compared with more traditional assessments made by an experienced rater.

3.10 PDM technique
In 1996, Al-Taani et. al. classified the bones of the hand-wrist images into pediatric stages of maturity using Point Distribution Models (PDM) [16]. The methods consisted of two phases: the training phase and the classification phase. During training, examples of bones from each class were collected to learn the allowable shape deformation for each class. A model representing each class was generated. These models were subsequently used to classify new examples of the bones. In classification, all models were compared to the input image and the object was assigned to the class whose model was the closest match. Classification was based on the closeness of fit for each model (mean shape). A PDM representing each stage of bone to be classified was generated. During classification, all models were fitted to the input bone. The quality of fit of each model is assessed using Minimum Distance Classifier as a fit measure, which showed the degree of correspondence of the model example with the bone. The system was tested by classifying two bones of the third finger (the third distal phalanx and the third middle phalanx). Two experiments were used to classify the third distal phalanx. The first experiment applied PDM to the third distal phalanx itself, and the second method applied PDM to its epiphysis. Comparing the results of the two experiments, it was concluded that the second experiment yielded better results.

3.11 Bone Labeling Technique
Wastl and Dickhaus proposed a pattern recognition based BAA approach, in the same year [17]. The approach consisted of four major steps: digitization of the hand radiograph, segmentation of ROI, prototype matching and BAA. First, the ROIs were the typical growing process of the bones became visible, were determined. ROIs comprised the metaphyses and epiphyses of the RUS bones namely, radius, ulna and short bones. Then the relevant bones were marked in the digital image. For further quantitative evaluation, they were normalized by rotating and scaling. The maturity stage of each bone was classified by correlating values of similarity between the bone and its corresponding prototype. The stage of the prototype with the highest correlation was taken as the estimated stage of the correlated bone. The advantage of the approach was the independence of the qualitatively characterized features of the TW2 method.

3.12 Bayesian and Regression Technique
Mahmoodi et. al. (1997) used knowledge based techniques in an automated vision system to assess the bone age. Knowledge-based Active Shape Models (ASM) were used to produce joint contour segmentation and description of the phalanx bones [18]. Three levels of object localization in a knowledge hierarchy were considered, namely, the hand silhouette, fingers and ultimately bones. Hand silhouette segmentation was easily achieved by a valley seeking algorithm to determine an appropriate intensity threshold from the image histogram. From the segmented hand silhouette, features such as finger convexities and concavities were obtained. Fingers were localized by landmarks generated from the above features using a peak-valley detection algorithm. These landmarks were used to generate window rectangles for each finger, to localize the phalangeal bones. Then a priori knowledge of the bone shape was used along with ASM to complete the segmentation, finally resulting in a closed contour. The hotelling transform used in ASM transformed the data from data space to feature space. The epiphysis shape descriptor of a phalanx is the most correlated parameter. Finally an age estimate was achieved by statistically modeling the shape and texture parameters in a data set using regression and Bayesian methods. The models were finally applied to test images in bone age estimation.

3.13 EMROI technique
Pietka et. al. conducted a computer assisted BAA procedure [19] by extracting and using the epiphyseal/ metaphyseal ROI (EMROI), in 2001. The system used two types of images: CR images and digitized images. Two preprocessing steps were performed- image orientation correction and background removal to increase the accuracy of ROI segmentation. Then with each phalanx 3 EMROIs were extracted which include: metaphysis, epiphysis and diaphysis of the distal and middle phalanges and for the proximal phalanges it includes metaphysis, epiphysis and upper part of metacarpals of proximal phalanges. The diameters of metaphysis, epiphysis and diaphysis of each EMROI were measured by extracting three lines within each EMROI. Various combinations of the above yield two features or indicators of development: 1) ratio of epiphyseal diameter divided by metaphyseal diameter and 2) epiphyseal

diameter divided by width of the gap between metaphysis and diaphysis. Accuracy of the system was measured independently at three stages, namely detection of phalangeal tip, extraction of EMROI and location of diameters and lower edge of EMROIs. The extracted features described the stage of skeletal development more objectively than visual comparison. Finally a time-frequency domain analysis was performed.

3.14 ASM technique
Niemeijer et. al. automated the TW method to assess the skeletal age from a hand radiograph. They made use of both shape and appearance information [20]. They employed an ASM segmentation method developed by Cootes and Taylor [21] to segment the outline of the bones. First the mean image for an ROI in each TW2 stage was constructed. Next an ASM was developed to determine the shape and location of the bones in a query ROI, so that this ROI can be aligned with each of the mean images in the third step. Then the correlation between a fixed area around the bones in the mean images and the query ROI was computed. These correlation coefficients were used to determine the TW2 stage in the final step. The points were chosen such that they were anatomical landmarks to be easily located in each image. They used the outline of metaphysis, epiphysis and diaphysis for this purpose. A large number of intermediate points were added to the epiphysis because it is a very important structure resulting in a shape of 81 landmarks. Then they aligned the mean image with the query image by Procrustes analysis, which was to transform the mean image without altering the shape of bones in it. The procedure obtained five correlation values for a query image. The TW2 stage was determined by taking the stage with the maximum correlation. Alternatively, the five values were used as features given as input to a trained Neural Network (NN) or Linear Discriminant (LD) classifier to obtain the matched stage as output. Results showed that the maximum correlation method gave the best performance while a 1-NN classifier and a LD classifier gave slightly poorer results. To improve the classification of query ROI, some extra features could be extracted from the ASM. To fully automate the TW2 method, it required to stage all the ROIs and to determine the positions of all the ROIs automatically.

3.15 Registration Technique
M.Fernandez et. al. [22] described a method for registering human hand radiographs for automatic BAA using the GP method. This method was the first step towards a segmentation-by-registration procedure to carry out a detailed shape analysis of the bones of the hand. It consisted of two registration stages: the first stage was a landmark-based registration procedure to build a wire model of a human hand out of a number of ordered landmarks and to match the landmarks of the template image onto the landmarks of the target image. The second stage was an intensity-based fine registration procedure to match the width of the fingers of the two images. Accurate results were obtained at a fairly low computational load.

3.16 Computing with words technique
A.Fernandez et. al. proposed a neural architecture for BAA [23]. In this system, they made use of fuzzy logic, a very flexible tool in classification to translate the natural language descriptions of the TW3 method into an automatic classifier. The system employed a computing with words paradigm, wherein the TW3 statements were directly used to build the computational classifier. It required only a few labeled radiographs to fine-tune the rules and to test the classifier. The maturity stage for each bone in TW3 was calculated from linguistic statements. The classifier was built upon a modified version of a fuzzy ID3 decision tree. The inputs to each tree were the features of its corresponding bone, and the output was its skeletal stage. The stages were numerically weighed following the TW3 method. The weighed summation was mapped onto the bone age. Results have shown that the method's performance was fairly high.

3.17 Active Contour technique
Luis Garcia et. al. presented a fully automatic algorithm [24] to detect bone contours from hand radiographs using active contours. First, segmentation of the bones of interest was done using active contours (snakes). It required determination of initial contours inside each bone of interest and then the use of the snakes to achieve the segmentation. The identified bones of interest, namely the phalanges and metacarpals, were segmented using successive tentative snakes. A novel truncation technique was employed to prevent the external forces of the snake from pulling the contour outside the bone boundaries. The results show that the performance of the algorithm was dependent on the resolution of the image (i.e.) an inherent lower limit in the resolution was required for the algorithm to work properly.

3.18 GVF Snakes Technique
Lin et. al. proposed a novel and effective carpal bone image segmentation method, to extract a variety of carpal bone features [25]. Prior to segmentation, anisotropic non-linear diffusion filtering was used to improve the signal to noise ratio. The principle was to smooth out the noise locally by diffusive flow and also prevent flow across object boundaries. A novel segmentation based on GVF model was used to find the boundary of the carpal bones. The steps involved were: (1)Input original image, (2)Anisotropic diffusion filter, (3)Edge map calculation, (4)GVF field calculation, (5)Initialize contour of carpal bones, and (6)Iterate the snake from the specified initialization contours. The experiments were carried out to examine the performance of GVF snake models on images of carpal bones and results were promising. This method could be extended and applied to other bone structures as well as to other images.

3.19 GSP Neural Network technique
Tristan and Arribas [26] designed an end to end system to partially automate the TW3 bone age assessment procedure in 2005. The system performed a detailed analysis of two important bones in TW3: the radius and ulna wrist bones. First, a modified K-means adaptive clustering algorithm was applied to segment the contours of the ROI. In feature extraction, up to 89 features were grouped into 4 sets: 48 Fourier features, 16 Zernike moments, 20 normalized wavelets and 5 normalized geometric features. LDA was employed in feature selection to reduce the dimensionality of input feature space. Finally bone age was estimated using a Generalized Softmax Perceptron (GSP) NN whose optimal complexity was estimated via the Posterior Probability Model Selection (PPMS) algorithm. The different development stages of radius and ulna were predicted from which the bone age of a patient was estimated in years. The mean estimated BA errors were the same order of magnitude and only slightly greater than mean radiologists'

discrepancies. But considering earlier samples of hand radiographs would yield better results.

3.20 Knowledge based technique

Zhang et. al. developed a knowledge based carpal ROI analysis method [27] for fully automatic carpal bone segmentation and feature analysis for bone age assessment by fuzzy classification. First, the carpal ROI were located and extracted by adaptive thresholding for further analysis. They applied anisotropic diffusion filter proposed by Perona and Malik [28] to differentiate carpal bones from the background. Next, edge detection by Canny edge detector [29,30] was performed, resulting in the detection of carpal bones. The carpal ROI includes carpal bones and parts of radius, ulna and metacarpals. So the carpal bones were identified by object refinement. All objects that touch the CROI borders were extracted and eliminated. A polar coordinate system with origin at the center of gravity of the Capitate (which was identified as the largest object) was built. The carpal ROI was then divided into five empirical regions. The positions of regions define the prior knowledge about where a carpal bone should be located in the carpal ROI. The first two bones which appear in chronological order, Capitate and Hamate were selected for further analysis. To describe the size and shape of the carpal bones, four morphological features, namely diameter, eccentricity, solidity and eccentricity were extracted from the above two bones. To simplify the feature space, all features which have the correlation above 0.60 were selected for BAA. The last step was to assess the bone age using fuzzy classification based on the extracted features. The three features, size, eccentricity and triangularity extracted from Capitate and Hamate each were taken as input to the fuzzy classifier. Using an automatic training algorithm, a CAD bone age was obtained for each of the above two bones. Final bone age was determined by the logic mean of the above two outputs. The defuzzification process used center of gravity to obtain the final CAD bone age. The CAD results were evaluated by comparison with readings and chronological age. The results verified the value of carpal ROI in assessment of skeletal development for young children.

3.21 Bone Xpert technique

1) Thodberg et. al. proposed a 100% automated approach called the Bone Xpert method [31]. The architecture of Bone Xpert divided the processing into three layers. Layer A to reconstruct the bone borders, Layer B to compute an intrinsic bone age value for each bone and Layer C to transform the intrinsic bone age value using a relatively simple post-processing.

3.22 DoG filter technique

Giordano et. al. [32] designed an automated system for skeletal bone age evaluation. The system extracted the EMROI by image processing techniques. The bones in the EMROIs, were extracted using the DoG filter and enhanced using a novel adaptive thresholding obtained by histogram processing. Finally, the main features of these bones were extracted for TW2 evaluation. The system does not depend strongly on the features of X-ray acquisition, hence is very versatile. Relying only on the analysis of the EMROI may not be sufficient for skeletal bone age evaluation. Future work required to implement the automated extraction and classification of the carpal bones.

3.23 SVM NN technique.

Hsieh et. al. [33] proposed an automatic bone age estimation system based on the phalanx geometric characteristics and carpal fuzzy information. The system was automatically calibrated by analyzing the geometric properties of hand images. Physiological and morphological features were extracted from medius image in segmentation stage. From the phalanx ROI and carpal ROI, features were extracted and classified as phalanx bone age and carpal bone age respectively. Classification employed back propagation, radial basic function and SVM neural networks to classify phalanx bone age. Normalized bone age ration of carpals was used to compute the fuzzy bone age. Carpal bones are significant parameters to depict bone maturity up to the age of 10. Whereas, after the age of 10, the phalanx features become significant. So the system combined the phalanxes and carpals for assessment. Also the application of NN classifiers along with fuzzy bone age confinement added to its effectiveness. The results indicated that the carpal information was a dominant feature, when the age of the child is less than 9 and the correct classification rate of SVM-P method remained unchanged implying that the phalangeal features have a wider effectiveness than the carpals.

3.24 PSO based template matching technique

Zhao Liu and Jian Liu proposed an automatic BAA method with template matching [34] based on PSO. First image preprocessing was done followed by edge detection using skeleton template matching. An edge set model was designed to store the middle information of image edge detection. So edge detection happened when and where it was necessary and the edge set increased during the matching. Priority was given for the bones which contribute more to the whole matching information, such as radius, ulna, metacarpal II, and phalange proximal II. The image template matching was based on PSO, followed by classification. TW3 classifier proposed by A.Fernandez et. al. (discussed in section 3.17) was made use of to obtain the bone age.

3.25 Automatic BAA using CROI and EMROI

Giordano et. al [35] presented an automatic system for BAA using TW2 method by integrating two systems: the first using the finger bones – EMROI and the second using the wrist bones – CROI. They ensure an accurate bone age assessment for the age range of 0-10 years for males and 0-7 years for females. The system employs novel segmentation techniques to segment the CROI and EMROI. Then for feature extraction, anatomical knowledge of the hand and trigonometric concepts are integrated. Then the TW2 stage is assigned by combining Gradient Vector Flow (GVF) Snakes and derivative difference of Gaussian filter. The effective algorithm used checks the compactness of the identified bones and separates them by using a curvature function. Thus even the fused carpal bones, such as Trapezium and Trapezoid are assessed. The proposed method represents a significant step forward in the automatic skeletal bone age measurement. Since the system is completely automatic, it does not require manual intervention by a radiologist. The method reaches very high performance in terms of both accuracy and sensitivity to image quality.

4. Analysis of BAA system

The value of a BAA system must ultimately be judged on the basis of its efficiency and accuracy. Additionally, speed of the processing in an important influencing factor. Basically, BAA procedure comprises the following phases: a) Image Pre-processing, b) ROI segmentation, c) Feature Extraction, d) Feature Selection and e) Classification. The nature of the techniques employed in each phase of the BAA procedure contributes to the overall efficiency. It is also evident that the ROI or the ossification center chosen is a competing factor to improve the speed and accuracy of the system. Since the predictive value of the ossification centers differs and changes during growth, research should be focused on the centers that best characterize skeletal development for the subject's chronological age. Gilsanz and Ratib [1] divided skeletal development into six categories and highlighted the specific ossification centers that are the best predictors of skeletal maturity for each group, as follows:

1) Infancy (the carpal bones and radial epiphyses);
2) Toddlers (the number of epiphyses visible in the long bones of the hand);
3) Pre-puberty (the size of the phalangeal epiphyses);
4) Early and Mid-puberty (the size of the phalangeal epiphyses);
5) Late Puberty (the degree of epiphyseal fusion); and
6) Post-puberty (the degree of epiphyseal fusion of the radius and ulna).

5. Research and Recommendations for future work:

A review of the factors influencing the total efficiency shows that there are some major aspects which appear to control the future trends of skeletal BAA. Research should be directed towards the identification of the combination of the following design and operational parameters in future developments in BAA systems:

a) Image acquisition – Proper positioning and orientation of the hand during image acquisition, appropriate exposure.
b) Preprocessing – Noise removal, background removal, image enhancement, increase of hand to background ratio.
c) Choice of ROI – Choosing ROI based on quality, density, size, shape, smoothness, thickness of border, etc.
d) Segmentation – Image transformation techniques, edge detection, bone outlining, ROI marking, object localization.
e) Feature extraction and selection – Identification of ROI parameters, feature identification, excluding irrelevant features, highlighting strong features, overlapping of features.
f) Classification – Feature analysis, assigning weightage for features, feature translation, choice of classifier, classification techniques, classifier analysis, result matching, suppression of misclassification, elevating of success rate, fine tuning.

6. Conclusion

On the basis of discussion in various sections, the following conclusions can be inferred:

- The assessment of skeletal maturity involves a rigorous examination of multiple factors and a fundamental knowledge of the various processes by which bone develops.
- Of all the indices describing the chronological situations of humans, such as height, dental age and bone maturity, bone age measurement plays a significant role because of its reliability and practicability in diagnosing diseases and growth disorders.
- Bone age is assessed based on a radiological examination of skeletal development of the left hand wrist.
- A discrepancy between the bone age and chronological age indicates abnormalities in skeletal development reflecting endocrinological disorders.
- In most children growth, puberty and related endocrine changes follow a well orchestrated pattern. The pace of maturation varies widely so that these events should be related to physical maturity rather than chronological age. Hence bone age reflects physical maturity and is considered as a sort of "biological age".
- Bone age is useful in the clinical evaluation of children with growth and puberty disorders.
- The main clinical methods for skeletal bone age estimation namely, the GP method and the TW method, and the various attempts to automate them are reviewed.
- High discrepancies in GP method are due to general comparison of radiograph with atlas patterns. A more detailed comparison of individual bones would yield ambiguous results.
- TW method yields the most reliable results and hence is more preferable inspite of its high complexity.
- The various BAA systems reviewed differ from each other based on: a)Preprocessing techniques, b)ROI identified, c) Segmentation procedure d)Features extracted and selected, and e)Classifiers.
- The techniques employed in each phase of the BAA procedure contribute to the overall efficiency of the system.
- Ossification centers are the best predictors of skeletal maturity or bone age. Hence they also influence the speed and accuracy of the BAA system.
- Since the predictive values of the ossification centers change during growth, those which best characterize the skeletal growth of the particular subject should be chosen.
- Thus the choice and application of optimal BAA techniques on the optimal ossification centers for the corresponding subject would yield excellent results.

References

1. Vicente Gilsanz, and Osman Ratib, *Hand Bone Age – A Digital Atlas of Skeletal Maturity*, *Springer-Verlag*, 2005.
2. Concetto Spampinato, "Skeletal Bone Age Assessment", University of Catania, Viale Andrea Doria, 6 95125, 1995.
3. R.K.Bull, P.D.Edwards, P.M.Kemp, S.Fry, I.A.Hughes, "Bone Age Assessment: a large scale comparison of the Greulich and Pyle, and Tanner and Whitehouse (TW2) methods, *Arch. Dis. Child*, vol.81, pp. 172-173, 1999.
4. J.M.Tanner, R.H.Whitehouse, *Assessment of Skeletal Maturity and Prediction of Adult Height (TW2 method)*, Academic Press, 1975.

5. Sankar K. Pal, and Robert A. King, "On Edge Detection of X-Ray Images using Fuzzy Sets", *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol.5, no.1, pp.69-77, 1983.
6. A.Kwabwe, S.K.Pal, R.A.King, "Recognition of bones from rays of the hand", *International journal of Systems and Science*, 16(4): 403-413, 1985.
7. Amita Pathak, S.K.Pal, "Fuzzy Grammars in Syntactic Recognition of Skeletal Maturity from X-Rays", *IEEE Trans. on Systems, Man, and Cybernetics*, vol.16, no.5, 1986.
8. David J. Michael, Alan C. Nelson, "HANDX: A Model-Based System for Automatic Segmentation of Bones from Digital Hand Radiographs", *IEEE Trans. on Medical Imaging*, vol.8, no.1, 1989.
9. E. Pietka, M. F. McNitt-Gray, and H. K. Huang, "Computer-assisted phalangeal analysis in skeletal age assessment," *IEEE Trans. Med. Imag.*, vol. 10, pp. 616–620, 1991.
10. S. M. Gam, K. P. Hertzog, A. K. Poznanski, and J. M. Nagy, "Metacarpophalangeal length in the evaluation of skeletal malformation," *Radiology*, vol. 105, pp. 375-381, 1972.
11. J. M. Tanner and R. D. Gibbons, "Automatic bone age measurement using computerized image analysis," *J. Ped. Endocrinol*., vol. 7, pp. 141–145, 1994.
12. E. Pietka, L. Kaabi, M. L. Kuo, and H. K. Huang, "Feature extraction in carpal-bone analysis," *IEEE Trans. Med. Imag*., vol. 12, pp. 44–49, 1993.
13. G. K. Manos, A.Y. Cains, I.W. Rickets, and D. Sinclair, "Segmenting radiographs of the hand and wrist", *Comput. Methods Programs Biomed.*, vol. 43, pp. 227–237, 1994.
14. S.N.C.Cheng, H.Chen, L.T.Niklason, R.S.Alder, "Automated segmentation of regions on hand radiographs", *Med. Phy.*, vol. 21, pp.1293-1300, 1994.
15. N.M.Drayer and L.A.Cox, "Assessment of bone ages by the Tanner-Whitehouse method using a computer-aided system, *Acta Paediatric Suppl.*, pp.77-80, 1994.
16. Al-Taani, A.T., Ricketts, I.W., Cairns, A.Y.,"Classification Of Hand Bones For Bone Age Assessment", *Proceedings of the Third IEEE International Conference on Electronics, Circuits, and Systems, ICECS '96*., pp.1088-1091, 1996.
17. Wastl, S., Dickhaus, H. : "Computerized Classification of Maturity Stages of Hand Bones of Children and Juveniles", *Proceedings of 18th IEEE International Conference EMBS*, pp.1155-1156, 1996.
18. Mahmoodi, S., Sharif, B.S., Chester, E.G., Owen, J.P., Lee, R.E.J.: "Automated vision system for skeletal age assessment using knowledge based techniques." *IEEE conference publication*, ISSN 0537-9989, issue 443: 809–813, 1997.
19. E. Pietka, A. Gertych, S. Pospiech, F. Cao, H. K. Huang, and V. Gilsanz, "Computer-assisted bone age assessment: Image preprocessing and epiphyseal/ metaphyseal ROI extraction," *IEEE Trans. Med. Imag.*, vol. 20, no. 8, pp. 715–729, Aug. 2001.
20. M. Niemeijer, B. van Ginneken, C. Maas, F. Beek, and M. Viergever, "Assessing the skeletal age from a hand radiograph: Automating the Tanner-Whitehouse method," *in Proc.Med. Imaging, SPIE*, vol. 5032, pp. 1197–1205, 2003.
21. T. F. Cootes, A. Hill, C. J. Taylor, and J. Haslam, "The Use of Active Shape Models for Locating Structures in Medical Images," in Proceedings of 13th Int. Conf. on IPMI, (London, UK), pp. 33–47, Springer-Verlag, 1993.
22. Miguel A. Martin-Fernandez, Marcos Martin-Fernandez, Carlos Alberola-Lopez, "Automatic bone age assessment: a registration approach", *Medical Imaging 2003: Image Processing, Proceedings of SPIE*, vol. 5032, pp. 1765-1776, 2003.
23. Santiago Aja-Fernandez, Rodrigo de Luis-Garcia, Miguel Angel Martın-Fernandez, Carlos Alberola-Lopez, " A computational TW3 classifier for skeletal maturity assessment: A Computing with Words approach", *Journal of Biomedical Informatics*, vol. 37, no.2, pp. 99–107, 2004.
24. R. de Luis, M. Martın, J. I. Arribas, and C. Alberola, "A fully automatic algorithm for contour detection of bones in hand radiographies using active contours," *Proc. IEEE Int. Conf. Image Process.*, vol. 2, pp. 421-424, 2003.
25. Pan Lin, Feng Zhang, Yong Yang, Chong-Xun Zheng, "Carpal-Bone Feature Extraction Analysis in Skeletal Age Assessment Based on Deformable Model", *Journal of Computer Science and Technology* , vol. 4, no. 3, pp. 152-156, 2004.
26. A. Tristan-Vega and J. I. Arribas, "A radius and ulna TW3 bone age assessment system," *IEEE Trans Biomed Eng*, vol. 55, pp. 1463–1476, 2008.
27. A. Zhang , A. Gertych , B. Liu, "Automatic bone age assessment for young children from newborn to 7-year-old using carpal bones", *Computerized Medical Imaging and Graphics* , vol. 31 , Issue 4 - 5 , pp. 299 – 310, 2007.
28. P. Perona, J. Malik, "Scale-space and edge detection using anisotropic diffusion", *PAMI 1990*, vol. 12, issue 7, pp.629-639, 1990.
29. J.F.Canny, "Finding edges and lines in images", Master thesis, Massachusetts Institute of Technology; 1983.
30. J.F.Canny, "A computational approach to edge detection", *IEEE Trans PAMI 1986*, 8(6): 679, 1986.
31. H. Thodberg, S. Kreiborg, A. Juul, and K. Pedersen, "The Bone Xpert Method for Automated Determination of Skeletal Maturity*", IEEE Trans Med Imaging*, vol. 28, no. 1, pp. 52–66, 2009.
32. D. Giordano, R. Leonardi, F. Maiorana, G. Scarciofalo, and C. Spampinato, "Epiphysis and Metaphysis Extraction and Classification by Adaptive Thresholding and DoG Filtering for Automated Skeletal Bone Age Analysis," *in Proc. of the 29th Conference on IEEE Engineering in Medicine and Biology Society,* pp. 6551–6556, 2007.
33. Chi-Wen Hsieh, Tai-Lang Jong, Yi-Hong Chou and Chui-Mei Tiu, "Computerized geometric features of carpal bone for bone age estimation", *Chinese Medical Journal,* 120(9):767-770, 2007.
34. Zhao Liu, Jian Liu, Jianxun Chen, Linquan Yang, "Automatic Bone Age Assessment Based on PSO", *IEEE*, 2007.
35. D. Giordano, C. Spampinato, G. Scarciofalo, R. Leonardi, "An Automatic System for Skeletal Bone Age Measurement by Robust Processing of Carpal and Epiphysial/Metaphysial Bones" *IEEE Trans. On Instrumentation and Measurement*, vol.59, issue 10, pp. 2539-2553, 2010.