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Skeletal Bone Age Assessment – Research Directions

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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.

I. 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.

II. 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]. A number of algorithms for automated skeletal bone age assessment exist in the literature.

III. DEVELOPMENTS OF BAA SYSTEMS

A. 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. This laid the foundation for automation of X-ray image analysis. They also proposed algorithms for automatic thresholding of grey levels using index of fuzziness and entropy of a fuzzy set.

B. 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. The input to the classifier was a set of primitives (as points, lines, segments, and curves) which had been previously extracted from hand X-ray and output was the maturity state of each bone.

C. 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. It used three stages: 1) Preprocessing stage 2) Segmentation stage and 3) Measurement stage. 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. Results obtained were to be compared with the traditional visual observation results. 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.

D. 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. The lower edge of the PROI was found by scanning a horizontal line on the thresholded hand image to search for the soft tissue junction between the thumb and the index. The upper edge was the horizontal line just at the tip of the third phalanx. 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. Then the third finger was separated from which the lengths of the distal, middle and proximal phalanx were measured. These measurements were converted into skeletal age by using the standard phalangeal length table proposed by Garn et.al [10]. The age associated with a single phalangeal length was obtained by a linear interpolation of the table values. These single bone age estimates were then averaged to assess the global phalangeal age of the patient. The algorithm was successful for 94% of cases. The 6% failure was for images where the soft tissue of the middle phalanx extends into the edge of the radiation field. The mean standard error was 08.mm. Phalangeal length, applied in the standard phalangeal length table, did not appear to be a sufficient indicator of skeletal maturity. An improved method was required for an objective measurement of the bone morphological features.

E. 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. CACAS had two limitations, as follows. First was that each bone had to be located manually, resulting in no gain in efficiency. Secondly, the templates were rigid, i.e. they could only change size, not shape and density. So some bones did not match well thus yielding incorrect results.

F. 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 standard position of the hand has to be fixed [12]. For this 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. Those features describe the size, shape and location. They also include some gray scale pixel value information.

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.

G. 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.

H. 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. The methods were tested on a database of 50 pairs of hand radiographs. They segmented the middle and index fingers with an average success rate of 83% per hand. For the segmented finger strips, they located ROIs on both the middle and the proximal phalanges correctly over 84% of the times. 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.

I. 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.

J. 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. Classification rates for the two experiments were 70.5% and 73.7% respectively. Misclassification was due to the similarity in the size and shape of the misclassified bones. The errors could be reduced by using some other features of the bones besides the PDMs.

K. 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. These markers help to determine the regions of interest automatically. The ROIs differ in size and position. 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 system was evaluated with a dataset of 280 radiographs. The classification rate for a specific bone was the ratio of the correctly classified ROIs to the total amount of ROIs of that bone and it is found to be in the range of 0.93 to 0.99. To improve the classification rate by 10%, morphological features like quotient of the width of the epiphysis to the width of the metaphysis were employed along with the prototype matching approach. The advantage of the approach was the independence of the qualitatively characterized features of the TW2 method.

The distinction between neighboring stages was difficult, since the stages were so similar that even experts were uncertain about which stage to choose. Also they suggested for a continuous scale for the growing process of a bone by analyzing the difference of correlation of neighboring prototypes.

L. Method Comparison Technique:

In 1999, Bull et. al. made a remarkable comparison of GP and TW2 methods [3] and concluded the following. The GP method involves a complex comparison of all of the bones in the hand and wrist against reference "normal" radiographs of different ages. In most institutions, a rapid modified version of this technique is used, whereby the overall appearance of a given radiograph is compared with the reference radiographs and the nearest match is selected. Although this modified approach is considerably faster than the original, it may be less accurate. The TW2 method relies on the systematic evaluation of the maturity of all the bones in the hand and wrist. Bull et. al. compared the rapid GP method with the TW2 method in a large group of subjects.

Data were analyzed using the more appropriate “method comparison” technique. Statistical analysis involved comparison of bone age assessed by the two methods and the results were plotted on a scatter graph. Similar statistical techniques were then used to assess 39 repeated studies to measure intra-observer variation. The comparison confirmed that the bone ages assessed with TW2 method were slightly greater than those measured with GP method. The measured intra-observer variation was greater for the GP method than for the TW2 method. This accounts for much of the discrepancy between the two methods. In GP method, the greatest potential source of error comes from the comparison of the overall appearance of the radiographs with the standard reference radiographs to obtain the best match. They concluded that the GP and TW2 methods produce different values for bone age, which are significant in clinical practice. They have also shown that the TW2 method is more reproducible than the GP method. They finally suggested TW2 method to be preferably used as the only one BAA method when performing serial measurements of a patient.

M. 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. The Bayesian method resulted in an average relative error of 8.93% which was reasonably low compared to the regression method.

N. 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. The procedure was applied to 200 clinical hand wrist radiographs. Phalangeal tip detection failed in 4% of radiographs, which was due to over or under exposure. For EMROI extraction, the gap between epiphysis and metaphysic was not marked in 4% of the cases. The accuracy of diameters extraction was evaluated using intersection of bones and location of end points and the results are tabulated. Finally a time-frequency domain analysis was performed.

O. 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. The system was tested with a database of 243 hand radiographs. 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.

P. 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.

Q. 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. They focused on the classifier itself, taking for granted the feature extraction. So it does not constitute an end-to-end classification system.

R. 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. Failures were due to low quality images, improper positioning of hands and also due to non-uniformities in the gray level values. Prior knowledge about the problem domain was necessary to develop a robust algorithm and a future extension was to focus on fine-tuning the snake energy terms for the metacarpals.

S. 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. After the preprocessing stage, 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.

T. 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. Since a neural classifier will not be capable of handling such a great number of features, a 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.

U. 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. The workflow of carpal ROI analysis procedure included seven steps. First, the carpal ROI were located and extracted by adaptive thresholding for further analysis. Carpal bones in the image were poor in contrast. Also, the bone edges were degraded by noise and artifacts. So 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. Then straight and short lines and spots were removed. The eccentricity of carpal bone was between 0.1 and 0.9 and was used as a prior knowledge. Then for model-based carpal bone identification, a post-processing procedure utilizing a prior knowledge was developed to identify the bones. 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. The growth of Capitate and Hamate slow down after the age 5.50 for male and 4 for female, and for such cases, carpal ROI does not reflect very accurate information. So the other bones which appear later than Capitate and Hamate could be considered to improve the accuracy of the system. The CAD bone age based on carpal ROI could be integrated with phalangeal ROI to provide more accurate BAA.

V. Bone Xpert Technique:

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. The bone reconstruction method automatically rejected images with abnormal bone morphology or very poor image quality. Bone XPert method comprised the following innovations:

a. a generative model for bone reconstruction
b. bone age prediction from shape, intensity and texture scores derived from PCA
c. the consensus bone age concept that defined bone age of each bone as the best estimate of the bone age of the other bones in the hand
d. a common bone age model for males and female
e. the unified modeling of TW and GP bone age.

W. 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. This system required less user feedback on system's setting. The system does not depend strongly on the features of X-ray acquisition, hence is very versatile. The system performance was evaluated over a private database of 20 hand images. 97% success was achieved in finger extraction, 86% in EMROI extraction, 50% for extraction of the proximal phalanx of the 5^{th} finger and 87% for classification. 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.

X. 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, which increased the classification error rate in Fuzzy C case. The correct classification rate of SVM-P method remained unchanged implying that the phalangeal features have a wider effectiveness than the carpals.

Y. 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. A data set of 60 hand-wrist images was used and the accuracy of the system was 0.93 years.

Z. 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. Also the system outperforms very effective method such as Bone Expert, by not rejecting any image in the database. The method reaches very high performance in terms of both accuracy and sensitivity to image quality.

IV. 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
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:

a. Infancy (the carpal bones and radial epiphyses);
b. Toddlers (the number of epiphyses visible in the long bones of the hand);
c. Pre-puberty (the size of the phalangeal epiphyses);
d. Early and Mid-puberty (the size of the phalangeal epiphyses);
e. Late Puberty (the degree of epiphyseal fusion); and
f. Post-puberty (the degree of epiphyseal fusion of the radius and ulna).

V. 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.

VI. CONCLUSION

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

a. The assessment of skeletal maturity involves a rigorous examination of multiple factors and a fundamental knowledge of the various processes by which bone develops.
b. 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.
c. Bone age is assessed based on a radiological examination of skeletal development of the left hand wrist.
d. A discrepancy between the bone age and chronological age indicates abnormalities in skeletal development reflecting endocrinological disorders.
e. 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".
f. Bone age is useful in the clinical evaluation of children with growth and puberty disorders.
g. 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.
h. 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.
i. TW method yields the most reliable results and hence is more preferable in spite of its high complexity.
j. The techniques employed in each phase of the BAA procedure contribute to the overall efficiency of the system.
k. Ossification centers are the best predictors of skeletal maturity or bone age. Hence they also influence the speed and accuracy of the BAA system.
l. 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.

m. Thus the choice and application of optimal BAA techniques on the optimal ossification centers for the corresponding subject would yield excellent results.

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