Comparative Study of Skeletal Bone Age Assessment Approaches using Partitioning Technique

P. Thangam
Assistant Professor/ CSE(PG)
Sri Ramakrishna Engineering College - Coimbatore

K. Thanushkodi
Director
Akshaya College of Engg & Technology - Coimbatore

T. V. Mahendiran
Assistant Professor/ EEE
Coimbatore Institute of Engg & Technology - Coimbatore

ABSTRACT
This paper presents the comparative study on four computerized skeletal Bone Age Assessment (BAA) methods using the partitioning technique. The four systems studied work according to the renowned Tanner and Whitehouse (TW2) method, based on the Region of Interest (ROI) taken from the wrist bones. The systems ensure accurate and robust BAA for the age range 0-10 years for both girls and boys. Given a left hand-wrist radiograph as input, they estimate the bone age by deploying remarkable techniques for pre-processing, feature extraction, and classification. The four BAA systems differ from each other in the type of ROI used, the feature extraction techniques and finally the classification. The systems output the age class to which the radiograph is categorized (Class A – Class J), which is mapped onto the final bone age. The systems were studied and their performances were compared by varying the partition of the train and test data sets. The systems were judged based on the results obtained from two radiologists.

Keywords
Skeletal Bone Age Assessment (BAA), TW2, radiograph, Classification, Partitioning.

1. INTRODUCTION
Bone age assessment is very significant in pediatrics, especially in the diagnosis of endocrinological problems and growth disorders [1]. Based on the skeletal development of the bones in the left-hand wrist, bone age is assessed and compared with the chronological age. A variation between these two values indicates abnormalities in skeletal development. This is used in diagnosis of endocrine disorders and also to monitor the therapeutic effect of treatment. Bone age indicates whether the growth of a patient is accelerating or decreasing, based on which the patient can be treated with growth hormones. BAA is widely used due to its simplicity, minimum radiation exposure, and the availability of multiple ossification centers for evaluation of maturity. 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. compared the GP and TW method and concluded TW method to be more accurate [3]. TW method uses a detailed analysis of each individual bone, allocating it to one of eight classes and assigning it a score based on its developmental stage. The sum of all scores results in the final bone age. The development of each ROI is divided into various stages, as shown in Fig. 1, 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 metaphysis
- Stage E – border of the epiphysis is concave
- Stage F – epiphysis is as wide as metaphysis
- Stage G – epiphysis caps the metaphysis
- Stage H – fusion of epiphysis and metaphysis has begun
- Stage I – epiphyseal fusion completed.

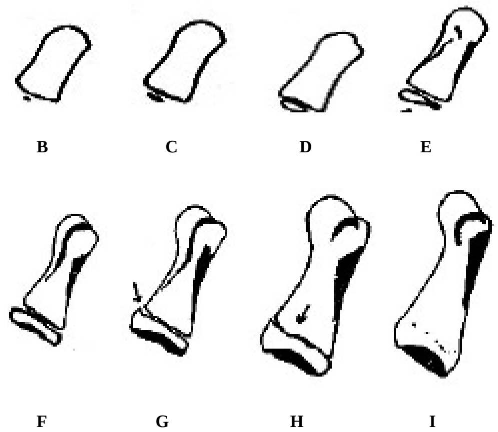

Fig 1: TW stages for proximal phalanx of thumb

By adding the scores of all ROIs, an overall maturity score is obtained which is correlated with the bone age differently for males and females [4].

2. RELATED WORK
In 1980s, Pal and King proposed the theory of fuzzy sets for edge detection in X-ray images [5]. Kwabwe et. al. in 1986, proposed certain algorithms to recognize the bones in an X-ray image of the hand and wrist [6]. Pathak and Pal [7] developed a fuzzy classifier for syntactic recognition of different stages of maturity of bones from X-rays of hand and wrist. Michael and Nelson [8] developed HANDX, a model-based system for automatic segmentation of bones from digital hand radiographs. This computer vision system, offered a solution to automatically find, isolate and measure bones from digital X-rays. Pietka et. al. described a method [9] based on independent analysis of the phalangeal regions, which was done in several stages by measuring the lengths of the distal, middle and proximal phalanx and converted into skeletal age by using the standard phalangeal length table

proposed by Garn et.al [10]. Tanner and Gibbons proposed the Computer- Assisted Skeletal Age Scores (CASAS) system [11]. Pietka et. al. conducted phalangeal and carpal bone analysis using standard and dynamic thresholding methods to assess skeletal age [12]. Cheng et. al. [13] proposed the methods to extract a region of interest (ROI) for texture analysis, 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. Drayer and Cox [14] 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. Al-Taani et. al. classified the bones of the hand-wrist images into pediatric stages of maturity using Point Distribution Models (PDM) [15]. Wastl and Dickhaus proposed a pattern recognition based BAA approach [16], which consisted of four major steps: digitization of the hand radiograph, segmentation of ROI, prototype matching and BAA. Mahmoodi et. al. used Knowledge-based Active Shape Models (ASM) in an automated vision system to assess the bone age [17]. Pietka et. al. conducted a computer assisted BAA procedure [18] by extracting and using the epiphyseal/ metaphyseal ROI (EMROI). From each phalanx, 3 EMROIs were extracted and the diameters of metaphysis, epiphysis and diaphysis of each EMROI were measured. Niemeijer et. al. [19] automated the TW method by constructing a mean image and using a query image to assess age. M.Fernandez et. al. [20] described a method for registering human hand radiographs for automatic BAA using the GP method. A.Fernandez et. al. proposed a fuzzy logic based neural architecture for BAA [21]. The system employed a computing with words paradigm, wherein the TW3 statements were directly used to build the computational classifier. Luis Garcia et. al. presented an automatic algorithm [22] to detect bone contours from hand radiographs using active contours. Lin et. al. proposed a novel and effective carpal bone image segmentation method using GVF model, to extract a variety of carpal bone features [23]. Tristan and Arribas [24] designed an end-to-end system to partially automate the TW3 bone age assessment procedure, using a modified K-means adaptive clustering algorithm for segmentation, extracting up to 89 features and employing LDA for feature selection and finally estimating bone age using a Generalized Softmax Perceptron (GSP) NN, whose optimal complexity was estimated via the Posterior Probability Model Selection (PPMS) algorithm. Zhang et. al. developed a knowledge based carpal ROI analysis method [25] for automatic carpal bone segmentation and feature analysis for bone age assessment by fuzzy classification. Thodberg et. al. proposed an automated approach called the Bone Xpert method [26]. 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. Giordano et. al. [27] designed an automated system for skeletal bone age evaluation using DoG filtering and a novel adaptive thresholding. Hsieh et. al. [28] proposed an automatic bone age estimation system based on the phalanx geometric characteristics and carpal fuzzy information. Zhao Liu and Jian Liu proposed an automatic BAA method with image template matching based on PSO [29]. Giordano et. al [30] presented an automatic system for BAA using TW2 method by combining Gradient Vector Flow (GVF) Snakes and derivative difference of Gaussian filter. We have presented a thorough survey of literature on BAA methods in our previous work [31], explaining in detail the various work done in BAA and providing directions for future research. Our previous work [32] describes a computerized BAA method for carpal bones, by extracting features from the convex hull of each carpal bone, named as the convex hull approach. We have also proposed an automated BAA method to estimate bone age from the feature ratios extracted from carpal and radius bones, named as the feature ratio approach [33]. Our decision tree approach utilizes features from the radius and ulna bones and their epiphyses for BAA [34]. We have also exploited the epiphysis/ metaphysis region of interest (EMROI) in BAA using our Hausdorff distance approach [35].

3. MATERIALS AND METHODS

The paper presents the comparative analysis of four different computerized approaches for BAA, based on the features from various wrist bones considered:

- Convex Hull approach using Carpal bone features
- Feature Ratio approach using Carpal and Radius bone features
- Decision Tree approach using Radius and Ulna features
- Hausdorff distance approach using Epiphysis/ Metaphysis features

The convex hull based approach [32] estimates the bone age from the carpal bones by determining the convex hull for each carpal bone and extracting three features from each of them namely, *Solidity*, *Convexity* and *Concavity*. The final classification is done by finding the closest match for the test feature set in the trained feature vector. The feature ratio approach [33] uses features extracted from the carpals and radius bone for BAA. From the extracted features, two feature ratios are computed, *CROI-Ratio* and *RROI*-Ratio, which are in turn used to find the mean feature ratios, *MCRatio* and *MRRatio*. The above two ratios of the test image is subtracted from those already stored in the feature vector. The class with the minimum values for both the differences is output as the final age class. The decision tree approach [34] makes use of epiphyseal features of the radius and ulna bone, namely *R_Presence*, *U_Presence*, *R_Diameter*, *R_Circularity*, *U_Circularity*, *R_Roughness*, *U_Roughness*, *R_Capping*, *U_Capping*, *R_Fusion*, and *U_Fusion*. These features are fed into the decision tree classifier, based on the gender and the output is the final bone age class to which the radiograph belongs. Hausdorff distance approach [35] extends the work done by Giordano et al [30] in estimating the bone age from EMROI joints. The system constructed the feature vector F_{Stage}^{Bone} from the features d_{meta}, $dnv1, \dots, dnv5$, $area1, \dots, area6$, and dh_{epi} along with three additional distance measures from the middle phalange EMROI of the 5th finger. This was to judge the degree of fusion of the epiphysis with the metaphysis. Finally the TW stage assignment was done by computing the minimum Hausdorff distance between the features extracted from the test image and the F_{Stage}^{Bone} feature vector.

For all the above four approaches the data set of images used were 220 images (110 male and 110 female). These 220 images were partitioned into training and testing images. For this, three types of partitions were applied, as shown in Table 1 and the results obtained for the four approaches in each case were analyzed and compared. The standard age classes used in all of the above approaches were Class A to Class J, the age group for each of the class varies from approach to approach. The input to the system was a radiograph image of size 200 X

300 pixels and the output was the age class (Class A – Class J) to which the image is classified into. The performances of the four approaches were measured in terms of four metrics, *precision%*, *recall%*, *specificity%* and *accuracy%*, based on the bone age results obtained from two radiologists. A comparative analysis of the performance of the four approaches was also conducted as part of the work.

Table 1. Partitions for data set

Partitions	Data Partition	
	Train Images	**Test Images**
Partition I	120	100
Partition II	160	60
Partition III	180	40

4. RESULTS AND DISCUSSION

As shown in Table 1, the partitioning technique [36, 37] applied for comparative analysis utilized three different partitions of data. When the number of images in the test data set and train data set where varied, the four BAA approaches showed differences in the performances in terms of all the four metrics, *accuracy%, specificity%, precision% and recall%.* Table 2 provides the performance results of the convex hull approach for each partition. Table 3 provides the performance results of the feature ratio approach for each partition. Table 4 provides the performance results of the decision tree approach for each partition. Table 5 provides the performance results of the Hausdorff distance approach for each partition.

The performance metrics are calculated using the following formulae:

$$precision = \frac{TP}{TP + FP} \tag{1}$$

$$recall = \frac{TP}{TP + FN} \tag{2}$$

$$specificity = \frac{TN}{TN + FP} \tag{3}$$

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

The convex hull approach showed excellent results of 100% for all the four performance measures for Partition II and Partition III. For Partition I, average performance was obtained, which was 98.5% *accuracy*, 99% *specificity*, 93% *precision* and 92% *recall*.

The feature ratio approach exhibited best performance for Partition III proving 100% for all performance metrics. Its performance for Partition II was also promising with 99% *accuracy*, 99% *specificity*, 95% *precision* and 94% *recall*. Partition I resulted in average performance of 98% *accuracy*, 99% *specificity*, 90% *precision* and 90% *recall*.

The decision tree approach was better than the feature ratio approach in producing 100% in all the four performance metrics for Partition III. The next best results were obtained for Partition II yielding 99% *accuracy*, 100% *specificity*, 92% *precision* and 93% *recall*. Average results were attained for Partition I which were 98% *accuracy*, 99% *specificity*, 90% *precision* and 91% *recall*.

The Hausdorff distance approach also showed excellent results for Partition III with 100% for all metrics, and slightly better results for Partition II, with 99.5% *accuracy*, 99% *specificity*, 95% *precision* and 94% *recall*. Average performance was achieved for Partition I with 98% *accuracy*, 99% *specificity*, 88% *precision* and 90% *recall*.

Table 2. Performance of Convex Hull approach for each partition

Performance Metrics	*Partition I*	*Partition II*	*Partition III*
accuracy%	98.5	100	100
specificity%	99	100	100
precision%	93	100	100
recall%	92	100	100

Table 3. Performance of Feature Ratio approach for each partition

Performance Metrics	*Partition I*	*Partition II*	*Partition III*
accuracy%	98	99	100
specificity%	99	99	100
precision%	90	95	100
recall%	90	94	100

Table 4. Performance of Decision Tree approach for each partition

Performance Metrics	*Partition I*	*Partition II*	*Partition III*
accuracy%	98	99	100
specificity%	99	100	100
precision%	90	92	100
recall%	91	93	100

Table 5. Performance of Hausdorff Distance approach for each partition

Performance Metrics	*Partition I*	*Partition II*	*Partition III*
accuracy%	98	99	100
specificity%	99	99	100
precision%	88	95	100
recall%	90	94	100

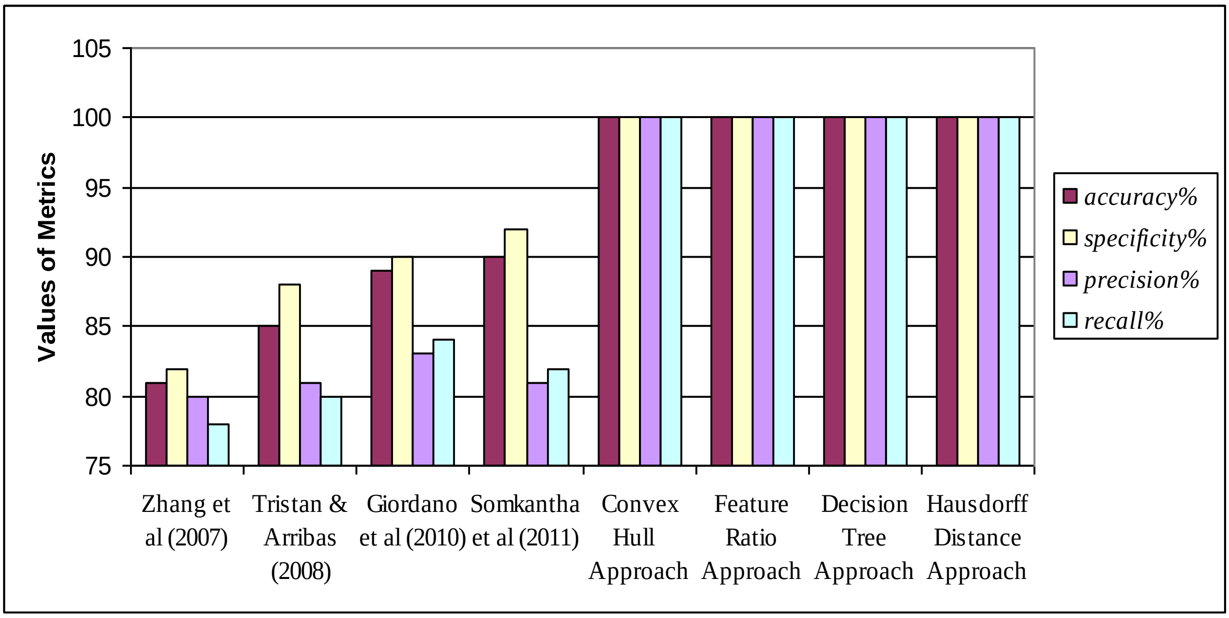

Fig 2: Comparison of Proposed systems with Existing systems

Based on the above observations, it is found that Partition III yields the best of the best results by scoring 100% for all the parameters, for all the four approaches. Partition II scores 100% in all parameters, for the convex hull approach. The reason for the slight deviation in results was sorted out as the classification of the radiographs into one year more or one year less than the actual class. From the literature and based on the suggestions from our radiologist experts, it is resolved that a difference of one year in age (Eg: If the radiologist classified it as B and our BAA system classified it as C), can be taken as correct classification because the error of one stage in a bone age system is clinically negligible. Hence the performances of the systems are analyzed by introducing a tolerance limit *ToL* of 1 year (i.e. *ToL* = ±1year). With the introduction of *ToL* = ±1year, all the four methods provided 100% in all the performance metrics, for both the partitions I and II. Thus all the four proposed systems achieve 100% success rate and their performances are compared with the existing systems in Fig. 2.

5. CONCLUSION

Despite the advances made in BAA, simplicity in design of the classifier and success rate in estimating the accurate bone age still remain as the main challenges for the technique. A large number of studies are carried out to identify best methods for bone age estimation. Four such BAA schemes have been developed for accurate bone age estimation by deploying simpler yet robust methods for feature extraction and classification. The approaches make use of diverse classification methods on different combinations of wrist bones. Medical studies reveal that a BAA system that utilizes the phalanges, carpal bones, radius and ulna bones forms a robust method for computerizing BAA throughout the entire age range (0-19 years of age). So there comes a necessity to incorporate all the important wrist bones in bone age estimation. This work presents four methods for BAA covering the most important wrist bones, namely the carpals, the EMROI of phalanges, the radius and the ulna. Morphological feature extraction is done in order to extract geometric features from the selected ROI bones, which describe the morphology of the bone. These features are utilized to train the system in classifying the radiograph into the corresponding age class, which is in turn mapped on to the final bone age. Future work will be focused on extending the system to work on the age group above 10 years, broadening the system to include the further TW2 bones such as ulna, phalanges, etc. and integrating the system with the clinical PACS.

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