

Full Length Research Paper

Skeletal bone age assessment from epiphysis/metaphysis of phalanges using Hausdorff distance

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The work explains an efficient method for skeletal bone age assessment (BAA) from the epiphysis/metaphysis of phalanges using Hausdorff distance as the measure for classification. The method was based on the Tanner and Whitehouse (TW2) method of BAA. The system guaranteed accurate BAA for the age range 0-10 years for both male and female. The input image was initially preprocessed and 8 EMROI joints were identified and cropped, which were segmented using difference of the Gaussian (DoG) method. 14 features were extracted from each EMROI and stored as feature vector. In addition, three distance parameters were extracted to compute the closeness of the epiphysis and metaphysis of the fifth finger middle phalanx as a measure of fusion. Finally, classification of the image into one of the ten bone age classes was done by measuring the Hausdorff distance between the trained feature vector and the feature set of the test image. The assigned age class (Class A – J), was then mapped onto the final bone age. The performance of the system was evaluated with the help of diagnosis done by two skilled radiologists. The system was very robust, achieving an accuracy rate of 98%, specificity rate 99%, precision rate 88%, and recall rate 90% when partitioning the dataset into 120 train images and 100 test images. When partitioned into 160 train images and 60 test images, the system scored 99% for accuracy, 99% for specificity, 95% for precision and 94% for recall. For the partition with 180 train images and 40 test images, the proposed method showed 100% results in all the four performance metrics.

Key words: Skeletal bone age assessment (BAA), TW2, radiograph, EMROI, epiphysis, metaphysis, Hausdorff distance, classification.

INTRODUCTION

Bone age is a way of describing the degree of maturation of child's bones. As a person grows from fetal life through childhood, puberty, and finishes growth as a young adult,

the bones of the skeleton change in size and shape (Hochberg, 2002). These changes can be seen by x-ray. The "bone age" of a child is the average age at which children reach this stage of bone maturation. A child's current height and bone age can be used to predict adult height. At birth, only the metaphyses of the "long bones" are present. As a child grows the epiphyses become calcified and appear on the x-rays, as do the carpal bones of the hands, separated on the x-rays by a layer of invisible cartilage where most of the growth is occurring. As sex steroid levels rise during puberty, bone maturation accelerates. As growth nears conclusion and attainment of adult height, bones begin to approach the size and

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Abbreviations: BAA, Bone age assessment; ROI, region of interest; DoG, difference of Gaussian; EMROI, epiphyseal/metaphyseal region of interest; TW, tanner Whitehouse; GP, Greulich Pyle; TP, true positive; FN, false negative; FP, false positive; TN, true negative.

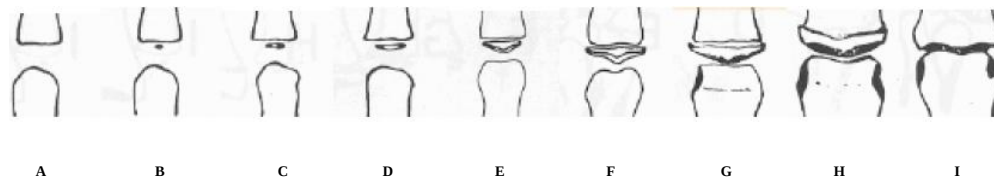


Figure 1. TW stages for phalanx EMROI.

shape of adult bones. The remaining cartilaginous portions of the epiphyses become thinner. As these cartilaginous zones become obliterated, the epiphyses are said to be "closed" and no further lengthening of the bones will occur. Pediatric endocrinologists are the physicians who most commonly order and interpret bone age x-rays and evaluate children for advanced or delayed growth and physical development (Oestreich, 2010; Gaskin and Kalm, 2011).

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 (Gilsanz and Ratib, 2005). 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.

RELATED WORK

The main clinical methods for skeletal bone age estimation are the Greulich and Pyle (GP) method and the Tanner and Whitehouse (TW) method. GP is an atlas matching method while TW is a score assigning method (Spampinato, 1995). GP method is faster and easier to use than the TW method. Bull et al. (1999) 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 the most accurate.

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 (Tanner and Whitehouse, 1975). 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. TW2 was a revision of TW1, especially in relation to the scores associated to each stage and also the difference between both sexes. In the TW2 method (Tanner et al., 1983), 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. TW3 method is an evolved version of TW2, which calibrates the bone age scoring method on the North American children (Tanner et al., 2001).

The development of each ROI is divided into discrete stages, as shown in Figure 1, and each stage is given a letter (A,B,C,D,...I), reflecting the development stage as:

1. Stage A – absent.
2. Stage B – single deposit of calcium.
3. Stage C – center is distinct in appearance.
4. Stage D – maximum diameter is half or more the width of metaphysic.
5. Stage E – border of the epiphysis is concave.
6. Stage F – epiphysis is as wide as metaphysic.
7. Stage G – epiphysis caps the metaphysic.
8. Stage H – fusion of epiphysis and metaphysis has begun.
9. Stage I – epiphyseal fusion completed.

By adding the scores of all ROIs, an overall maturity score is obtained.

Michael and Nelson (1989) developed a model-based system for automatic segmentation of bones from digital hand radiographs named as HANDX. This computer vision system, offered a solution to automatically find, isolate and measure bones from digital X-rays. Pietka et al. (1991) described a BAA method based on independent analysis of the phalangeal regions. Phalangeal analysis was performed in several stages by measuring the lengths of the distal, middle and proximal phalanx. These measurements were converted into skeletal age by using the standard phalangeal length table proposed by Garn et al. (1972). These single bone age estimates were then averaged to assess the global phalangeal age of the patient. Tanner and Gibbons (1994) introduced the Computer- Assisted Skeletal Age Scores (CASAS). 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. Two or three most similar templates for the radiographs were identified. 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.

Pietka et al. (1993) performed phalangeal and carpal bone analysis using standard and dynamic thresholding methods to assess skeletal age. Cheng et al. (1994) proposed a method to extract a region of interest (ROI) for texture analysis, with particular attention to patients with hyperparathyroidism. The techniques included multi-resolution sensing, automatic adaptive thresholding, detection of orientation angle, and projection taken perpendicular to the line of least second moment. In the same year, Drayer and Cox (1994) 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. Al-Taani et al. (1996) classified the bones of the hand-wrist images into pediatric stages of maturity using Point Distribution Models (PDM). Wastl and Dickhaus (1996) proposed a pattern recognition based BAA approach which consisted of four major steps: digitization of the hand radiograph, segmentation of ROI, prototype matching and BAA. Bull et al. (1999) made a remarkable comparison of GP and TW2 methods and concluded the following. The GP method involved a complex comparison of all of the bones in the hand and wrist against reference "normal" radiographs of different ages. Although this approach was considerably faster than the original, it may be less accurate. The TW2 method relied on the systematic evaluation of the maturity of all the bones in the hand and wrist. The measured intra-observer variation was greater for the GP method than for the TW2 method. This accounted for much of the discrepancy between the two methods. They also concluded that the GP and TW2 methods produce different values for bone age, which were significant in clinical practice. They had also shown that the TW2 method was more reproducible than the GP method. They finally suggested TW2 method to be preferably used as the only BAA method when performing serial measurements of a patient. Mahmoodi et al. (1997) used Knowledge-based Active Shape Models (ASM) in an automated vision system to assess the bone age. Pietka et al. (2001) conducted a computer assisted BAA procedure by extracting and using the epiphyseal/metaphyseal ROI (EMROI). From each phalanx 3 EMROIs were extracted which include: metaphysis, epiphysis and diaphysis of the distal and middle phalanges, and for the proximal phalanges it included metaphysis, epiphysis and upper part of metacarpals of proximal phalanges. The diameters of metaphysis, epiphysis and diaphysis of each EMROI were measured. The extracted features described the stage of skeletal development more objectively than visual comparison. Niemeijer et al. (2003) automated the TW method to assess the skeletal age from a hand radiograph. They employed ASM previously defined by Cootes et al. (1993) to segment the outline of the bones. Then the mean image for a 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 could 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.

Martín-Fernández et al. (2003) described a method for registering human hand radiographs for automatic BAA using the GP method. They used a segmentation-by-registration procedure to carry out a detailed shape analysis of the bones of the hand. Accurate results were obtained at a fairly low computational load. Aja-Fernández et al. (2004) proposed a fuzzy logic based neural architecture for BAA. The system employed a computing with words paradigm, wherein the TW3 statements were directly used to build the computational classifier. Luis-García et al. (2003) presented a fully automatic algorithm to detect bone contours from hand radiographs using active contours. Lin et al. (2004) proposed a novel and effective carpal bone image segmentation method using Gradient Vector Flow (GVF) model, to extract a variety of carpal bone features. Tristán-Vega and Arribas (2008) 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) Neural Networks (NN), whose optimal complexity was estimated via the Posterior Probability Model Selection (PPMS) algorithm. Zhang et al. (2007) developed a knowledge based carpal ROI analysis method for fully automatic carpal bone segmentation and feature analysis in bone age assessment by fuzzy classification. Thodberg et al. (2009) proposed a 100% automated approach called the Bone Xpert method. 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. (2007) designed an automated system for BAA using Difference of Gaussian (DoG) filtering. The bones in the EMROIs, were extracted using the DoG filter and enhanced using an adaptive thresholding obtained by histogram processing. Finally, the main features of these bones were extracted for TW2 evaluation. Hsieh et al. (2007) proposed an automatic bone age estimation system based on the phalanx geometric characteristics and carpal fuzzy information. From the phalanx ROI and carpal ROI, features were extracted and used in estimating phalanx bone age and carpal bone age respectively. Phalanx bone age was estimated using radial basis function and SVM NN and carpal bone age was estimated using fuzzy logic. Liu et al. (2007) proposed an automatic BAA method with template

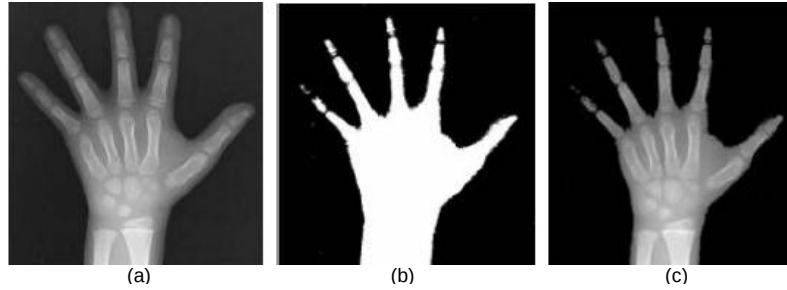


Figure 2. (a) Input Image (b) Thresholded Image (c) Superimposed Image.

matching based on Particle Swarm Optimization (PSO). An edge set model was designed to store the middle information of image edge detection. The image template matching was based on PSO, followed by classification. TW3 classifier proposed by Aja-Fernandez et al. (2004) was made use of to obtain the bone age. Mart'ın-Fern'andez et al. (2009) proposed a landmark-based elastic registration procedure named articulated registration. The method registered individual bones affinely and soft tissue elastically so that long skeletal structures were maintained straight while a continuous and smooth transformation was obtained all over the image. They also proved that the proposed articulated registration outperformed the alternatives based on Thin-Plate Splines (TPS). Giordano et al. (2010) 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. Then the TW2 stage was assigned by combining Gradient Vector Flow (GVF) Snakes and DoG filtering. Our previous work (Thangam et al., 2012a) describes a computerized BAA method for carpal bones, by extracting features from the convex hull of each carpal bone and applying them to estimate the bone age. We have also estimated the bone age from carpal and radius bone feature ratios (Thangam et al., 2012b).

MATERIALS AND METHODS

The proposed work is an extension of the EMROI bone age assessment system developed by Giordano et al. (2010). In the existing system the authors have preprocessed the radiograph by applying Difference of Gaussian (DoG) filter, followed by segmentation. Then, a vector of features was extracted, as follows;

$$F_{Stage}^{Bone} = [d_{meta}, dist_m_1, dnv_1, dnv_2, \dots, dnv_5, dh_{epi}, area1, area2, \dots, area6] \quad (1)$$

where d_{meta} was the width of the metaphysis, $dnv_1, \dots, dnv_5$ were the heights of different lines that divide the epiphysis width into six equal parts, $area1, \dots, area6$ were the areas of the six identified parts, $dist_m_1$ was the distance between the metaphysis and the diaphysis, and dh_{epi} was the width of the epiphysis. Finally the TW stage assignment was done by simply calculating the minimum Euclidean distance between the features extracted from the test image and the F_{Stage}^{Bone} feature vector. The system achieved an

overall success rate of 90% for EMROI bone stage assignment. But the drawbacks of the existing system were:

1. The system does not cover the age range of 8-10 years for females, and
2. It did not exploit the fusion of the EMROI for the BAA process.

The proposed work was an extension of the above system. The EMROI analysis section was followed, including the pre-processing and extracting of F_{Stage}^{Bone} . In addition, we have extracted 3 more distance measures from the middle phalanx EMROI of the 5th finger. This was to judge the degree of fusion of the epiphysis with the metaphysis. It is because the middle phalanx of the 5th finger is the last EMROI to appear and ossify; we have concentrated on this particular EMROI joint to bridge the gap in the existing system. Thus our proposed method works for the age range of 0-10 years for both males and females, and also we have taken into account the degree of fusion of the Epiphysis and Metaphysis for bone age estimation.

Image pre-processing

The input image was thresholded and superimposed onto the original image to remove hand borders. Figure 2 depicts samples for input, thresholded and superimposed images. From the pre-processed image, 8 EMROI joints were identified and cropped, which include 2 EMROI of thumb + 3 EMROI of middle finger + 3 EMROI of 5th finger. Each cropped EMROI was processed further by applying DoG (Difference of Gaussian) filter, which is done as follows. 2 Gaussian filters with different standard deviation (1 and 1.5) are applied and the two resultant images are subtracted to obtain an image with enhanced contours. Thresholding was applied on this image, followed by segmentation. Figure 3 depicts the cropping of the 3 EMROI of the middle finger and the final preprocessed distal phalanx EMROI of the middle finger. Figure 4 shows the series of preprocessing done on the cropped EMROI.

Feature extraction

From the preprocessed EMROI, 14 features were extracted as done in the existing system to obtain the feature vector F_{Stage}^{Bone} . In addition, three distance parameters, ED_1 , ED_2 and ED_3 were measured from the middle phalanx of the 5th finger. They were computed as the Euclidean distance between the epiphysis and the metaphysis of the 5th finger middle phalanx, as shown in Figure 5. The mean of ED_1 , ED_2 and ED_3 features was calculated an

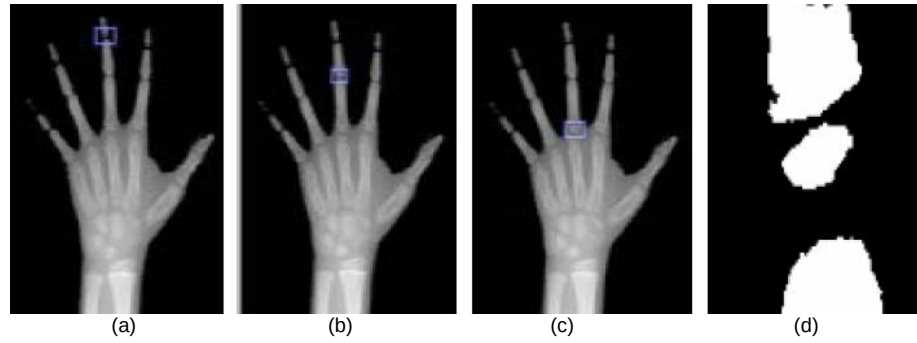


Figure 3. Cropped EMROI of (a) distal, (b) middle and (c) proximal phalanges of the middle finger (d) Segmented EMROI of the middle finger distal phalanx.

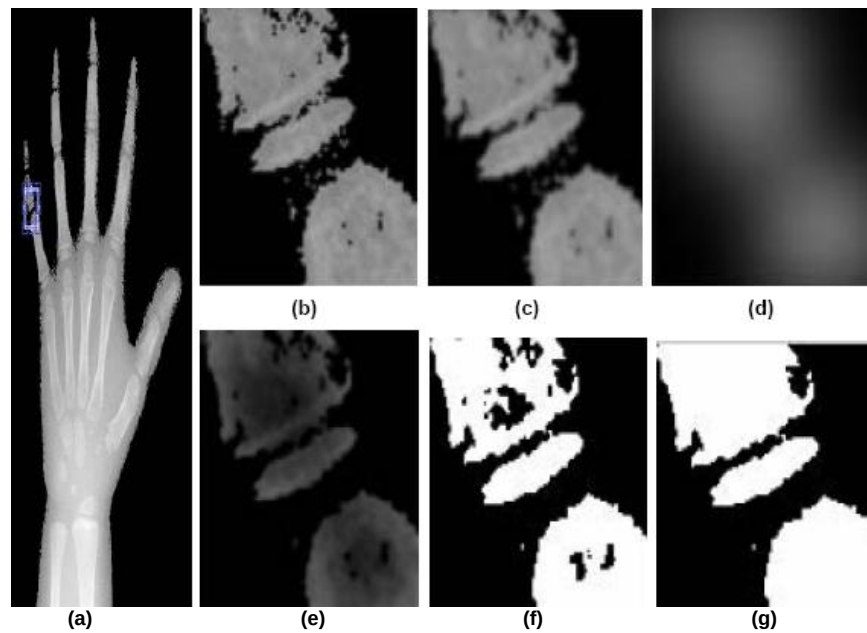


Figure 4. (a) Cropping of EMROI of the fifth finger middle phalanx (b) Cropped EMROI (c) Gaussian filtered image (Standard Deviation = 1) (d) Gaussian filtered image (Standard Deviation = 1.5) (e) Subtracted image (f) Thresholded image (g) Segmented EMROI.

assigned to *MED* (Mean Euclidean Distance). Hence, the new feature vector constructed here in the existing system is given as follows;

$$Fnew_{Stage}^{Bone} = [d_{med}, dist_m_1, dnv_1, dnv_2, \dots, dnv_5, dh_{epi}, area1, area2, \dots, area6, MED] \quad (2)$$

Classification

Feature extraction is followed by either the training phase or testing phase of classification (Duda et al., 2002). In case of training, the $Fnew_{Stage}^{Bone}$ is computed for all the 8 EMROI joints for each age group (1-10 years). This is conducted for both male and female

cases. Based on the values of $Fnew_{Stage}^{Bone}$, the radiograph is classified to the output skeletal class or category. The output class is chosen by calculating the Hausdorff distance between the $Fnew_{Stage}^{Bone}$ of the test image and that stored as trained data. The selected class is then mapped onto the skeletal bone age, based on the criteria shown in Table 1.

Data sets

The database consists of totally 220 images, of which 110 are male images and 110 female. The system was trained with 6 male and 6 female radiographs for each age group, thus with a total of 120

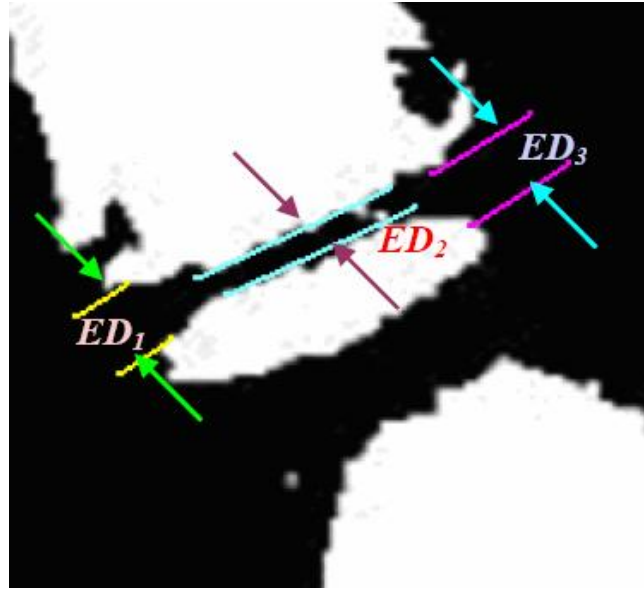


Figure 5. Computing of the distance measures ED_1 , ED_2 and ED_3 .

Table 1. Criteria selection.

S/N	Category	Values v (Years)
1.	Class A	0 year $< v < 1$ year
2.	Class B	1 year $< v < 2$ years
3.	Class C	2 years $< v < 3$ years
4.	Class D	3 years $< v < 4$ years
5.	Class E	4 years $< v < 5$ years
6.	Class F	5 years $< v < 6$ years
7.	Class G	6 years $< v < 7$ years
8.	Class H	7 years $< v < 8$ years
9.	Class I	8 years $< v < 9$ years
10.	Class J	9 years $< v < 10$ years

This Table provides the criteria of age range values for an input radiograph to get classified into any of the 10 age classes, Class A to Class J.

radiographs, 60 male and 60 female cases. Subsequently, 50 radiographs of male and 50 of female were used for testing.

RESULTS

The performance of the proposed system in estimating the bone age was evaluated using a test dataset consisting of 100 radiographs (50 for boys and 50 for girls). Much attention was dedicated to design and implement robust techniques for preprocessing and reliable feature extraction. The ease and accuracy of feature extraction for the proximal EMROI were slightly challenging when compared to the distal and middle EMROI, the reason being that these bones were

comparatively interior. The accuracy of the classifier was measured in terms of four metrics, *precision*, *recall*, *specificity* and *accuracy*. The above four metrics were measured for each class A – J, by computing True Positive(TP), False Negative(FN), False Positive(FP), and True Negative(TN) cases.

The performance metrics are calculated using the following formulae:

$$precision = \frac{TP}{TP + FP} \quad (3)$$

$$recall = \frac{TP}{TP + FN} \quad (4)$$

$$specificity = \frac{TN}{TN + FP} \quad (5)$$

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

Table 2 provides the values of True Positive, False Positive, False Negative and True Negative obtained for each age class, Class A to Class J. It also tabulates the computed values of the metrics which were used in estimating the precision, recall, specificity and accuracy used in evaluating the performance of the system. The performance of the system was validated by using the diagnoses results obtained for the data set from two radiologists. The class-wise performance of the system is depicted in the graph shown in Figure 6. The system achieved an accuracy rate of 98%, specificity rate 99%,

Table 2. Classification metrics.

Class	TP	FP	FN	TN	TP+FP	TP+FN	TN+FP	TP+TN+FP+FN
A	10	0	0	80	80	80	80	80
B	10	0	0	80	80	80	80	80
C	9	1	0	81	81	81	81	81
D	9	2	2	81	81	81	81	81
E	8	1	1	82	82	82	82	82
F	8	2	1	82	82	82	82	82
G	8	2	2	82	82	82	82	82
H	8	1	1	82	82	82	82	82
I	9	1	2	81	81	81	81	81
J	9	2	1	81	81	81	81	81

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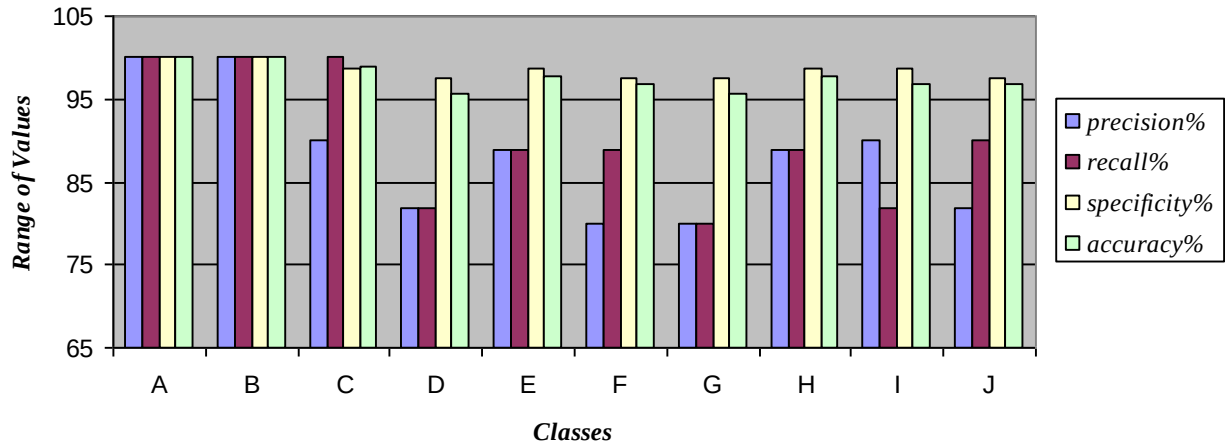


Figure 6. Performance Metrics Graph explains the performance of the system in terms of precision%, recall%, specificity% and accuracy% for each age class Class A to Class J.

precision rate 88%, and recall rate 90%.

DISCUSSION

Our implementation of the existing system (Giordano et al., 2010), which employed the F_{Stage}^{Bone} feature vector and Euclidean distance as the comparison metric produced an overall success rate of 89% for our data set. When we utilized the F_{Stage}^{Bone} feature vector and applied Hausdorff distance for comparison between the feature set of the test image and the trained F_{Stage}^{Bone} , an overall accuracy rate of 91% was obtained. This was due to the computation of the largest minimum distance between the two feature vectors using maximum and minimum distance measures. Though this had produced a better result than the existing system, there were some shortcomings to be

addressed, such as not considering the age range of 8-10 years for females and not utilizing the degree of fusion of the epiphysis and metaphysis. So we further extended our system to include additional features describing the above said fusion. As mentioned already, the middle phalanx of the 5th finger is the last EMROI to appear and ossify. Particularly, this bone contributed much to differentiate between the classes for 8-10 years in girls. So, investigating on this particular EMROI joint bridged the gap in the existing system. This led to the extraction of three additional features from the middle phalanx of the 5th finger, ED_1 , ED_2 and ED_3 and their mean MED was computed. When this MED was used in the F_{Stage}^{Bone} , more promising results were obtained. From the values of the metrics plotted in Figure 6, it is found that the minimum value of precision is 80% and obtained for the classes F and G and that of recall is 80% obtained for class G. The minimal value obtained for specificity is

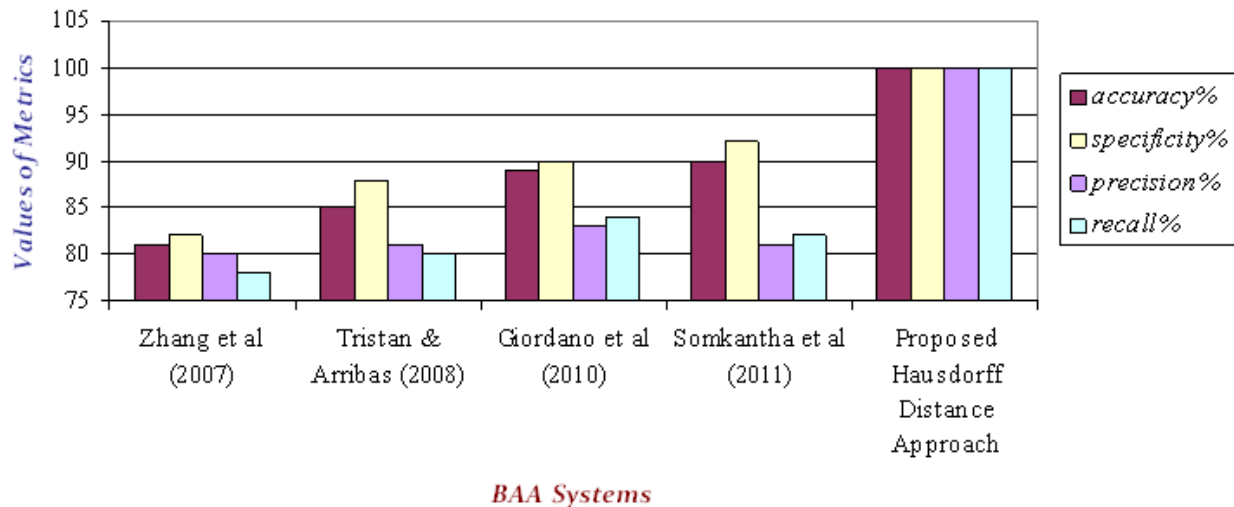


Figure 7. Comparison of the proposed Hausdorff Distance approach with the existing systems.

98% obtained for classes D, F, G and J and that of accuracy is 96% obtained for the classes D and G. Classes F and G found to downgrade the overall performance of the classifier, the reason being very minute difference between the measured features for the neighbors F and G, and G and H. Best performance was found in the earlier classes A and B, since there are very few ossified bones and good inter-class difference. The system achieved an accuracy rate of 98%, specificity rate 99%, precision rate 88%, and recall rate 90%. Thus the proposed BAA method based on EMROI features using Hausdorff distance performed far better when compared to the existing method. In order to improve the performance of the proposed method, the data set was partitioned into 160 train images and 60 test images, for which the proposed Hausdorff distance method scored 99% for accuracy%, 99% for specificity%, 95% for precision% and 94% for recall%. Further improvements in the results were obtained for the partition with 180 train images and 40 test images, in which case the proposed method showed 100% results in all the four performance metrics. Thus the proposed Hausdorff distance method for BAA has outperformed the existing systems, which is depicted in the comparison graph shown in Figure 7.

Conclusion and future work

An efficient system for bone age assessment using features extracted from EMROI bones has been developed. The adopted approach was found reasonably appropriate for the age group of 0-10 years since the main wrist bones that contribute toward BAA at that stage, namely the EMROI bones were considered here. The proposed bone age estimation procedure using Hausdorff distance proved to be efficient for the age

group of 0-10 years for both male and female cases, when validated with the results obtained from two radiologists. Future work will be focused on extending the system to work on the age group above 10 years, and broadening the system to include the further TW2 bones such as carpals, radius, ulna, etc. and also merging the system with Picture Archiving and Communication System (PACS).

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