Segmenting Bone Parts for Bone Age Assessment using Point Distribution Model and Contour Modelling

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Abstract. Bone age assessment (BAA) is a task performed on radiographs by the pediatricians in hospitals to predict the final adult height, to diagnose growth disorders by monitoring skeletal development. For building an automatic bone age assessment system the step in routine is to do image pre-processing of the bone X-rays so that features row can be constructed. In this research paper, an enhanced point distribution algorithm using contours has been implemented for segmenting bone parts as per well-established procedure of bone age assessment that would be helpful in building feature row and later on; it would be helpful in construction of automatic bone age assessment system. Implementation of the segmentation algorithm shows high degree of accuracy in terms of recall and precision in segmenting bone parts from left hand X-Rays.

1. Introduction

To solve complex real world problems and challenges, the scientific communities focus on building specialized machine learning algorithms but these algorithms can work effectively only if appropriate datasets are first created and pre-processed to suit the machine learning algorithms. These features are normally based on evaluation of single or multiple predictor variables. In case of bone age assessment the predictors normally are the dimensions, size and gaps between the different bones of specific part of skeleton such as wrist and hands. By using bone age charts and atlases [1], data analysis is often performed in a highly manual and subjective manner using very limited automatic image analysis and it depends more on the skill and experience of the bone age assessor and the process also suffers from inter-rater variability problems and other biases that affect the calibrations of bones’ dimensions. Hence, there is the need of automatic bone age assessment systems [2][3][4].

2. Related Work

According to the recent citations, it has been observed that the computation on human bones to access their maturity itself is a challenge. This can be attributed to many factors such as ossification and fusion of different hand bones at different stages but the main determinants are their races, diet habits, environment etc. Hence, region wise bone age charts or atlases should be built [1]. Technically, the image processing functions such as noise removal, background subtraction, soft tissue identification have undergone many changes to finally arrive at the set of measurement for accessing bone age[6]. Evaluation of the threshold based methods for segmentation has not resulted in fair degree of accuracy but adaptive thresholding methods may provide better results. Many algorithms are unable to find...
gradient difference in the soft tissue[7] for segmenting the bone parts. The region growing and merging methods are the methods that are dependent on the similarity[8] metric and connectivity[9] that carries a risk of fusing the epiphysis sites (situated around the metaphysis [2]). Secondly, region-based segmentation is insensitive to the semantics of the bone parts in the image. In simple words, it means that it does not recognize the membership based on pre-defined membership functions (defining the bone part). Each bone part, if considered as homogenous region[5] does not work well as per assumption that bone is formed by cancellous bone and cortical bone that has high variations on texture and intensity range. Some authors have worked on segmenting carpal bones [9] and deformable models such as active contour, active shape modeling[10][11][12] and active appearance modeling. In bio-medical application most the shapes of the organs, bones parts are not simple morphological boundaries and but have complex or arbitrary geometries. For, such it is always desirable to build a training dataset using a medical expert. Thus, in this research, these well established, proven methods are proposed to be used for bone part(s) segmentation as it will allow building of specific shape & approach models for each bone part using medical expertise.

3. Designing of algorithm for segmenting bone parts
In this section, the method employed for determining the edges of different bone structure/part has been discussed [figure 1]. There is a need to build a separate Point Distribution Model to segment each bone part[14][15] that can help to identify the contours[16][10] or boundaries of the each object so that it can finally be segmented into separate frames for further feature analysis. It should also be noted that all images undergo a preprocessing steps to make them standardized and workable. The x-ray image of left hand has been adjusted into a square of 800x600 consisting of full left hand image and 240x240 pixel of particular anatomical region.

3.1. The formulation of the local edge boundary: Landmarks or anchor points are marked on the image that represent the boundary of bone part in the following manner :

a) Let ‘Imp. n’ number of major land mark points ‘Imp’ manually clicked.
b) Let (Imp.x, Imp.y) be the location of the landmark points clicked.
c) Let Imp.I be variable representing the Image of Bone Part.
d) Interpolate to get more pairs of points (Imp.x,Imp.y).
e) Mark the Landmark points with 1, other points as zero.
f) Interpolate new set of landmark points and evenly space them.

Figure 1(a). Anatomical Locations of the bones parts in hand.(b) X-Ray of 18 Year Old Subject
Figure 2: Major Landmarks of Distal Phalanges and Meta Carpals bones

This process is a method of understanding the distribution of data points in a vector space model. These landmark points[15] are the most prominent points from which the shape of the bone part can be drawn given a locus. These points (x, y) become instances of the training set.

This collection of landmark points (anchor points) is the mean geometry of the shape of the bone part [Figure 2] with statistical model. It has been empirically found that the shape of bone instances varies statistically but the key features of the bone shape remain more or less same. Therefore, the constitute of bone shape is its data points represented using mathematical functions. This step gives the landmarks data points and the lines representing dataset which is divided into training and validation datasets.

3.2. Formulating the contour shape based model: The distribution of data points forms a contours or a distinct boundary [Figure 2]. In this step a new image is constructed by matching the statistical model of the bone part and its appearance model. The images with multiple scales are taken and the model is built from smaller scale to largest scale. Due to this multiple-resolutions approach variations in the data need to be smoothen and the construction of the shape model starts with the following steps.

a) Translation: In this process, image is translated so that the mean of the objects points lies on the centroid of the object.

Landmarks_data_points= (|[lnn.x1, lnn.y1], [lnn.x2, lnn.y2]|...),

The mean of these points is Xmean = (lnn.x1+ lnn.x2 + lnn.xi)/i, Ymean = (lnn.y1+ lnn.y2 + lnn.yi)/i

Translate, such that the mean is translated into origin (lnn.x1, lnn.y1, Ymean,y1)

b) Scaling: Likewise, the scale is removed by re-scaling the object so that root mean square distance from the point to be translated to origin 1.

S = mean (lnn.x- Xmean.xi)/ (lnn.y- Ymean.yi),this division will make the scale 1 when the point coordinates are divided by the Bone part image object scale.

c) Rotation: Initially it involves computing the angle to center of all points and then subtracting the mean angle to build new data points that have same rotation.

3.3. Formulating the shape of the bone part: In this function the texture of the image is wrapped and aligned using Piecewise linear transformation.

3.4. Representing and measuring the variation of each segment of bone part:

Step 1: Compute the mean and variance of the data.
Step 2: Compute eigenvectors; retain 98% of the variation.

Step 3: Define matrix U from the top t eigenvectors.

Step 4: Approximation.

3.5. Learning Shape model and allowing variation of each Bone part segment.

4. Evaluation of the segmentation algorithm

For the complete validation of the segmentation, recall and precision metrics were computed with twenty one images as shown in Table 1 and 2.

The Recall values Table 1&2 show the proportion of correct and valid images segmentation that can be used in bone age process made by the system out of full database of twenty one segmented images.

| Random Set ID | Number of Images | Image Type | Precision | Recall  |
|---------------|------------------|------------|-----------|---------|
| 1             | 2                | Distal     | 2/2 =1    | 2/21=0.095 |
| 2             | 3                | Distal     | 2/3 =0.66 | 2/21=0.095 |
| 3             | 4                | Distal     | 3/4 =0.75 | 3/21=0.144 |
| 4             | 5                | Distal     | 5/5= 1    | 5/21=0.239 |
| 5             | 6                | Distal     | 6/6=1     | 6/21=0.288 |
| 6             | 5                | Distal     | 4/5=0.8   | 6/21=0.298 |
| **Average**   |                  |            | **0.8683**| **0.1867**|

Figure 3. Graph for Distal phalanges Segmentation Evaluation
Table 2. Meta-Carpal Segmentation Evaluation

| Random Set ID | Number of Images | Image Type     | Precision | Recall |
|--------------|-----------------|----------------|-----------|--------|
| 1            | 2               | Meta Carpel    | 2/2 = 1   | 2/21 = 0.095 |
| 2            | 3               | Meta Carpel    | 3/3 = 1   | 3/21 = 0.144 |
| 3            | 4               | Meta Carpel    | 3/4 = 0.75 | 3/21 = 0.144 |
| 4            | 5               | Meta Carpel    | 3/5 = 0.6  | 3/21 = 0.144 |
| 5            | 6               | Meta Carpel    | 3/6 = 0.5  | 3/21 = 0.144 |
| 6            | 5               | Meta Carpel    | 5/5 = 1    | 5/21 = 0.238 |
| Average      |                 |                | 0.808     | 0.151  |

Figure 4. Graph Representing Number of Images Selected from different sets

It is also found that high degree pre-selection (with help of medical expert) and pre-processing of the images have also lead to the minimization of complications involved identification of the hand bone development of children. The choice of retaining minimum number of Eigen values leads to construct fairly good model, hence leads to good segmentation output. Variation in hand structural positioning has lead to inaccuracies also. It can be seen from the table 1 & 2 the average precision remains above 0.86 in case of distal and 0.808 in case of metacarpal bones. The values of recall follow a similar pattern with respect to the precision values. The values of recall remain small when the evaluation is considered from full dataset. Care has been taken to build random sets of images called the evaluation set out of the segmented images. In total 42 images were segmented, 21 images for distal and 21 for Meta carpal bones.

5. Conclusion
This research work addresses methods and strategies that are employed for the segmentation of the bone parts from the X-ray image of full hand. These segmented images will be useful for the bone age assessment. Hence, the primary focus of the paper has been to build and efficient method of image ROI segmentation using custom models for each part. In real life conditions also, as mentioned in the introductory section that inter-rater differences make the bone age process vulnerable to many error that may have some legal and medical implication not expected. These days parents taking this bone age assessment simply to get prediction how much eventually their ward would be taller and see if that augured well for the competitive sports or just to find if there is some "constitutional growth and Pubertal delay (CGPD). The applications are many and not just restricted for detection bone diseases. In cases where precocious puberty occurs and advance bone formation take place then standard atlas, procedure and automated software may run into error. Therefore, some cases become typical in nature for the doctors and subject’s chronological age must also be considered for correct assessment. The
algorithm works with few parameter tuning in each bone part model and the training is based on optimization methods with robust outcomes. The utilization of prior expected knowledge helps to build better models. The algorithms is relatively resistant to noise due to selection of high quality of images for training set. Then, the algorithm is adaptive in nature and optimally feasible for commercial applications of bone age assessment systems that may be built on cloud technologies. These models created here will reduce the manual work based on which researchers can build BAA in future.

6. References

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