Computer-Aided Detection (CADx) for Plastic Deformation Fractures in Pediatric Forearm

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A B S T R A C T

Bowing fractures are incomplete fractures of tubular long bones, often observed in pediatric patients, where plain radiographic film is the non-invasive imaging modality of choice in routine radiological workflow. Due to weak association between bent bone and distinct cortex disruption, bowing fractures may not be diagnosed properly while reading plain radiography. Missed fractures and dislocations are common in accidents and emergency practice, particularly in children. These missed injuries can result in more complicated treatment or even long-term disability. The most common reason for missed fractures is that junior radiologists or physicians lack expertise in pediatric skeletal injury diagnosis. Not only is additional radiation exposure inevitable in the case of misdiagnosis, but other consequences include the patient’s prolonged uncomfortableness and possible unnecessary surgical procedures. Therefore, a computerized image analysis system, which would be secondary to the radiologists’ interpretations, may reduce adverse effects and improve the diagnostic rates of bowing fracture (detection and quantification). This system would be highly desirable and particularly useful in emergency rooms. To address this need, we investigated and developed a new Computer Aided Detection (CADx) system for pediatric bowing fractures. The proposed system has been tested on 226 cases of pediatric forearms with bowing fractures with respect to normal controls. Receiver operation characteristic (ROC) curves show that the sensitivity and selectivity of the developed CADx system are satisfactory and promising. A clinically feasible graphical user interface (GUI) was developed to serve the practical needs in the emergency room as a diagnostic reference. The developed CADx system also has strong potential to train radiology residents for diagnosing pediatric forearm bowing fractures.

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1. Introduction

Plastic bowing fractures of children are called incomplete fractures in the forearm (radius and/or ulna). Clinical terminology was first defined by Borden in 1975 [3] based on the following unique features of fractures compared to other bone fractures as: 1) there exists a relative elasticity in the pediatric forearm long bone, 2) if an extensive axial force is applied to the bone, 3) the bone may undergo a bowing deformation, and 4) eventually followed by fracture. Plain radiographs are usually the choice of modality for evaluating bowing fractures. Other imaging techniques, such as ultrasound, CT and MRI, can also be helpful, but are in no means the clinical standard [4,5]. In routine radiological evaluation of these fractures by plain films, the imaging feature of the bowing fracture is excessively bended bone with an absence of cortex disruption [6,7]. Since a bowing fracture can be quite difficult to diagnose, radiologist may readily miss the cases with inconspicuous bending in space [1,2,8]. The consequences may include prolonged uncomfortableness, additional x-ray exposures, and possible surgery procedures.

To determine the degree of excessive bending, films of the contralateral uninjured forearms were used as comparison standards because the radius and ulna in healthy children may bend slightly [3,6,7]. This approach raises some clinical difficulties with scenarios of both forearms injured, unavailable contralateral radiographs, or available but not equivalent field of view (FOV). In addition, both anteroposterior (AP) and lateral (LAT) projections are necessary, because the bowing may only be visible in one projection.

In order to clarify the ambiguity between bowing and a bowing fracture, clinicians have tried different methods to describe the classification criteria quantitatively. Angulation is one of the
frequently used methods in describing forearm fractures [2,9–17]. Angulation measures the angle at the “suspected” fracture point (called angular point) formed by the two pieces of bones on each side of the fracture point. However, angulation may fail to provide an accurate measurement when a bowing deformity does not show an angular point. Measuring malunion of a radius in an AP view radiography is another method used to describe fractures [18]. This method was originally developed for adults, but later adopted to analyze natural bowing of the radius in healthy children in AP view films [19]. For ulnar plastic deformation, a similar method was proposed by Lincoln and Mubarak in 1994 [20,21].

This method used the maximum ulnar bow and its location to assist in the recognition of radial-head dislocation. A 3D method has also been designed for complicated and severe deformities, which are usually not apparent in 2D radiographs. In these cases, CT scans were required for both the fractured arm and the contralateral arm [23–25]. Since then, there has been little or no improvements in the computational aspect of bowing fracture diagnosis, mostly due to the relatively low frequency of such cases in emergency rooms, and lack of enough interest in the domain [22]. However, the nontrivial consequences of misdiagnosis make this problem worthy of attention.

With the rapid development of computer technology, computer-aided-diagnosis/detection (CAD) has been widely used in many diseases spanning from lung cancer to prostate cancer. One of the objectives in CAD design is to reduce observational oversights and false negative rates. Radiologists/orthopedists have also adopted CAD techniques in the diagnostic processes to detect bone tumors or fractures. Successful CAD systems include routine clinical application for bone metastases [26], surgical planning for orbital fractures [27], detection of long bone fractures, and real-time surgical localization for long bone fractures [28–30]. For bowing fractures, a CT-based method was reported [31]. By superimposing a deformed ulna onto the normal ones, reconstructed 3D CT images of forearm bones allow for measurement of the deformity in the AP, LAT, and axial planes. Results from the method successfully elucidated mechanisms of such an injury, indicating that traumatic bowing deformities of the ulna involved rotation rather than bending. However, there lacks systematic and quantitative assessments of the bowing fracture for both radius and ulna without comparison to the uninjured contralateral bones, particularly when only plain radiographic films available. Thus, it is highly desirable to create such a CAD system for pediatric forearm bowing fracture.

Herein, we propose a computerized image analysis of bowing fractures on plain-film with quantitative support for a radiologists’ diagnostic decisions. The outcome of this investigation is a Computer Aided Detection (CADx) system featuring a semi-automated bone extraction preprocess followed by analyzing two quantitative assessment parameters. Results from statistical analysis for each projection (AP and LAT view) and each bone (radius and ulna) are also presented. The developed CADx system's sensitivity and selectivity are summarized and presented by receiver operating characteristics (ROC) curves.

2. Materials and methods

2.1. Data

With the IRB approval, plain radiographs of children aged 1–18 years old were retrospectively collected. A total of 226 plain radiographs of forearms subjected to pediatric trauma were reviewed by two expert radiologists with over 10 years of experience. There were 59 diagnoses of bowing fractures, and all others were reported as normal (89 AP projections, 78 LAT projections). For the normal cases, no radius or ulna bowing deformity was found in the AP or LAT view. For abnormal cases, a bowing deformity may exist in either radius or ulna, in either or both of the AP and LAT views. Thus, for a systematic analysis, normal and abnormal cases are divided into 4 groups, by bone (radius/ulna) and by field of view (AP/LAT), respectively:

**Normal groups:** radius in AP view, radius in LAT view, ulna in AP view, ulna in LAT view

**Abnormal groups:** radius in AP view, radius in LAT view, ulna in AP view, ulna in LAT view

2.2. Preprocessing for bone extraction

Pediatric forearm bone fractures include bowing fractures and buckle fractures. This report is focused on the discussion on bowing fractures. We noticed that the radius or ulna in pediatric forearms always have some degrees of bending, regardless of the presence of bowing fractures or not. This feature inspired us to investigate the curvature of these bones. In order to measure the curvature, we extract the bowing portion and exclude the buckle portion from the radius/ulna. In other words, we need first to select the same piece of anatomically equivalent bone from every patient. However, in order to create a uniform processing protocol, it is necessary to define where the “cutting” point is, which is the first question we answer.

In this study, we designed and implemented a semi-automated bone extraction method that is based on the radius of curvature (R). R is a measurement of a curve function’s radius that best approximates the curve at that point, defined by an analytical equation:

\[ R = \frac{1 + \left(\frac{dy}{dx}\right)^2}{\frac{d^2y}{dx^2}}^{1/2}. \]

where y is the curve function with respect to variable x. In other words, a point’s bending degree on a curve, called curvature, is assessed by a measurement-circle’s radius. The radius is related to the curve function by Eq. (1). This definition intuitively states that the more “bending” of the curve, the smaller radius of curvature; the “flatter” the curve, the larger radius of curvature. Anatomically, the location with the maximum radius curvature matches the location where the buckle starts. We describe the bone extraction processing as follows:

Before the measurement, the image is rotated to a reasonable direction (for convenient and comfortable visualization). We then use a rectangular “crop” tool to extract either the radius bone or the ulna bone. The extracted bones must have a clear outside boundary of the radius (ORB) or outside boundary of the ulna (OBU). The process is demonstrated in Fig. 1. On the extracted bone image, we first collect the coordinate (x, y) for each point on the OBR/OBU through edge detection. These coordinates will be fitted into a function \( y = f(x) \), where \( f \) is a 6th-degree polynomial. We then calculate the radius of curvature R(x) for each point (x-coordinate) on the boundary of the bone based on Eq. (1), which is plotted in Fig. 2. The x-coordinates for the two maximum R(x) values are the cutting points for bone extraction.

Using a polynomial to perform curve fitting is a common approach in science and engineering applications. The degree of a polynomial for curve fitting is regulated by the feature/nature of the curve. If the “inherent feature/nature” of the curve does not have a known definition, the degree of the polynomial should then be practical in the application. Through 226 cases, we notice that R(x) monotonically increases or decreases when the function is a polynomial of 6th–degree or lower. A higher-degree polynomial will reduce the error for \( y = f(x) \) curve fitting, however, will also increase the number of local maximums (turbulence) for R(x). In order to minimize the curve fitting error and maintain the robustness of the method, we used the 6th–degree polynomial for all cases. The R(x) curve usually appears as a double-peak distribution which is corresponding to two buckle starting locations. The bone is automatically cut at these two points where \( R \approx \infty \) or reaches a local
maximum (Fig. 2). Outside of these two points, the buckle starts. The ulna in AP/LAT view usually shows a single-peak distribution. Thus, we combine the anatomical features of ulna (before the ulna coronoid process) to determine the cutting point for all cases. This extraction procedure makes data collection in a consistent and comparable format. Table 1 shows the case number for each group after semi-automated extraction.

2.3. Definition of measurement parameters

After cutting, the extracted bone from each subject will be anatomically equivalent for comparisons. The data points \((x,y)\) on the extracted bone boundary will be used for analysis. We define and use two parameters, in terms of central angle (CA) and circle curvature (CC), to evaluate the degree of bending of bones (Fig. 3). We briefly describe the parameters as follows:

Central Angle (CA): We first fit all data points on the extracted bone into a circle with optimal center-\(x\), center-\(y\) and radius (linear regression). The angle subtended by the arc that covers all data points is defined as the central angle (CA).
Circle Curvature (CC): The circle curvature (CC) is defined as the reciprocal of radius of curvature. The description for radius of curvature was provided in previous section (Eq. (1)). Since the curve function is a circle function (CA), the radius of curvature is indeed the radius of the circle. Therefore, \(CC = 1/R\). The CC has a similar transition trend as CA, i.e., the "flatter" the bone is (corresponding to a large \(R\)) the smaller value of CA or CC.

2.4. Comparison experiment

In order to validate the reliability of using radius of curvature for bone extraction and the measurement parameters (central angle and circle curvature), we conducted a comparison study by using a "simulated-manual" bone extraction procedure. The simulated extraction was based on the computed extraction points by adding/subtracting a random number of pixels \((\leq 10)\) to/from these points to mimic manual extraction's uncertainty. After such an extraction procedure, all subject bones were also examined by the CA and CC parameters.
Finally, we use an independent two-sample t-test to evaluate the effectiveness of each parameter for each paired group. At the end, we plot the ROC curves to find the best threshold value for each paired group.

2.5. GUI and processing procedure

We implemented the above mentioned method into a graphical user interface (GUI). Fig. 4 illustrates the GUI, which facilitates the following functions: (1) input/output of radiographic images, (2) image pre-processing, (3) image extraction, and (4) calculation of statistical parameters and data analysis. The GUI was originally created in Matlab, but compiled and built into a standalone application, which can be executed on any platform running any operating system.

3. Results

3.1. Statistical analysis

We first measured and calculated two parameters for all cases. Data show that obvious differences exist between normal groups and bowing fracture groups for both parameters. 95% confidence intervals (CI) of CA and CC for each group are listed in Table 2. Independent two-sample t-test was used to examine the statistics for the collected data. Outcomes show that both CA and CC parameters can effectively distinguish bowing fracture from normal bone in all paired comparisons (p < 0.05 for all cases). However, the CA and CC parameters cannot consistently show the same results on the bones by the simulation method and the simulation method through CA and CC can effectively differentiate bones with bowing deformity from normal bones.

3.2. ROC curve

After we confirmed that CA and CC were sensitive in detecting bowing deformity, we can determine the best threshold value for each paired group by constructing the ROC curves. We used half of the samples in each group to plot ROC curves and the other half of the samples to test the thresholds. For the normal group, data were randomly selected. However, because the abnormal group’s sample size is too small to support random selection, we first ranked them in a numerical order (based on the values of CA or CC), and then selected every other one as the initial data set. In Fig. 5, ROC curves for CA and CC were plotted at various threshold settings, ranging from 0 to 45° for CA (step size is 1°), and 0-250 k/pixel for CC (step size is 5 k/pixel). The ROC curve of CA is obviously closer to the upper left corner than the ROC curve of CC, indicating that CA is a better predictor for bowing fracture.

Based on the ROC curve of CA, a threshold value can be determined for this CADx system. In this study, we used the median value between normal and abnormal groups as a threshold (e.g., 13.59° for radius in AP view). We adopted this mechanism, defined as the optimal area under the curve (AUC), to determine all threshold values in this study. Table 4 shows the best threshold value determined by AUC and accuracy rate tested by the other half of data for each paired group. Both the AUC and accuracy rate of the test show that thresholds generated from the ROC curves of CA are greatly credible, better than CC, which even reached point (0, 1) in ROC space for radius and ulna in LAT view. CA is also overwhelmingly better than CC in the accuracy rate.

4. Discussion

Pediatric forearm bowing fractures can be easily misdiagnosed if the radiographic images were not read by a pediatric-radiologist. In the CADx approach, the first difficulty encountered is the un-biased data acquisition. The developed bone extraction method based on radius of curvature calculation has shown to be a reliable approach. In this study, we investigate the effectiveness of two parameters to quantitatively assess bowing deformation of children forearm without comparing with the contralateral arm. We demonstrate that both CA and CC can effectively differentiate bones with bowing deformity from normal bones. A comparison study between the proposed bone extraction method and the simulation method through CA and CC parameters further validated the method’s robustness (Table 3). In terms of sensitivity and selectivity, CA is a more reliable parameter than CC. In addition, CA is also a “scale-invariant” parameter, which is independent of image resolution. In plain radiography, FOV is associated with the size of the object. Therefore, CC is impacted by the image scale. Our next development for the CADx system will generate an age-based database by using both CA and CC parameters.

In addition to the rotation tool associated with the developed GUI, a manual segmentation tool and a graphical editing tool are also provided. These manual tools are used to handle special cases, such as overlapped bones. The CADx system has two potential immediate applications. First, it can be applied to an emergency room as a diagnostic reference. Pediatric forearm trauma may require orthopedic and radiology specialists for final diagnosis. However, an emergency room usually lacks such specialists. This CADx system can provide a...
second opinion" to radiologists. Second, the system can serve as a training platform. Our current system has included more than two hundred cases of plain radiography images from the database in the Dept. of Radiology, University of Miami Miller School of Medicine. We will include more cases to build a training system for radiology residents. Residents will randomly select cases from the database, give their trial diagnoses, and run the system to verify their trials.

5. Conclusion

This study introduced a semi-automated bone extraction method which reduced the error in manual measurement and created normalized data sets for statistical comparisons. We defined and investigated two parameters to assess bowing fractures in pediatric forearm. The results show that CA and CC can effectively detect bowing in radius/ulna by optimal threshold values to

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**Table 2**

95% of CI (confidence interval) of CA and CC for each group are presented. Note that 1) CA was measured and calculated unit of degrees, 2) CC was measured in unit of pixels. However, since curvature is reciprocal of radius of curvature, CC’s unit is 1/pixel after calculation. A constant of 1000 (k) was used to scale three parameters in a similar "comparable" level for data reading only.

<table>
<thead>
<tr>
<th>Type</th>
<th>Radius (AP view)</th>
<th>Radius (LAT view)</th>
<th>Ulna (AP view)</th>
<th>Ulna (LAT view)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CA (unit: °)</td>
<td>normal</td>
<td>10.27 ± 0.91 (n=40)</td>
<td>8.42 ± 1.00 (n=40)</td>
<td>7.09 ± 0.98 (n=37)</td>
</tr>
<tr>
<td></td>
<td>abnormal</td>
<td>17.64 ± 1.64 (n=17)</td>
<td>17.83 ± 3.41 (n=15)</td>
<td>22.93 ± 5.56 (n=11)</td>
</tr>
<tr>
<td>CC (unit: 1000/pixel)</td>
<td>normal</td>
<td>36.81 ± 4.91 (n=40)</td>
<td>30.42 ± 5.22 (n=40)</td>
<td>34.46 ± 6.05 (n=37)</td>
</tr>
<tr>
<td></td>
<td>abnormal</td>
<td>77.40 ± 26.94 (n=17)</td>
<td>66.66 ± 20.61 (n=15)</td>
<td>99.55 ± 42.32 (n=11)</td>
</tr>
</tbody>
</table>

---

**Table 3**

Comparisons for assessment parameters CA and CC yield significant difference (p < 0.05) between normal and abnormal groups (all views) consistently by the radius curvature based bone extraction method. However, the CA and CC parameters lost sensitivity when the bones were extracted by simulated manual extraction (< ± 10 pixel variations on the automated extraction points) between normal and abnormal groups.

<table>
<thead>
<tr>
<th>Analysis Parameter</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central Angle (CA)</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Based on curvature extraction</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Central Angle (CA)</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Based on simulation extraction</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Circle Curvature (CC)</td>
<td>0.006</td>
</tr>
<tr>
<td>Based on curvature extraction</td>
<td>0.006</td>
</tr>
<tr>
<td>Central Curvature (CC)</td>
<td>0.237</td>
</tr>
<tr>
<td>Based on simulation extraction</td>
<td>0.086</td>
</tr>
</tbody>
</table>

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**Table 4**

Threshold values obtained from the ROC curves are presented, where AN (accurate normal) is the accuracy rate for the normal group (negative accuracy), AA (accurate abnormal) is the accuracy rate for the abnormal group (positive accuracy), and AUC is the area under curve, for each paired group.

<table>
<thead>
<tr>
<th>Analysis Parameter</th>
<th>Threshold</th>
<th>AN</th>
<th>AA</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central Angle (CA)</td>
<td>Radius(AP)</td>
<td>13</td>
<td>90%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>Ulna(AP)</td>
<td>13</td>
<td>94%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>Radius(LAT)</td>
<td>14</td>
<td>95%</td>
<td>86%</td>
</tr>
<tr>
<td></td>
<td>Ulna(LAT)</td>
<td>14</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Circle Curvature (CC)</td>
<td>Radius(AP)</td>
<td>53</td>
<td>90%</td>
<td>66%</td>
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<tr>
<td></td>
<td>Ulna(AP)</td>
<td>53</td>
<td>67%</td>
<td>60%</td>
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<td>Radius(LAT)</td>
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</tr>
<tr>
<td></td>
<td>Ulna(LAT)</td>
<td>45</td>
<td>80%</td>
<td>100%</td>
</tr>
</tbody>
</table>

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Fig. 5. Receiver operating characteristic curves show the sensitivity (TPR: true positive rate) and selectivity (FPR: false positive rate) for the assessment parameters of CA and CC. Optimal threshold value for each paired group can be determined by using ROC curve. ROC curves of CA are obviously closer to the upper left corner than CC, which means CA is a better predictor for bowing fracture compared to CC.
distinguish bowing deformity from normal bone. The optimal threshold values, derived from ROC, improve diagnostic reliability and accuracy. The CADx system can be potentially applied in emergency rooms and be used as residency training software.

Conflict of interest statement

All authors (Yuwei Zhou, Uygar Teomete, Ozgur Dandin, Onur Osman, Taner Dandinoglu, Ulas Bagci and Weizhao Zhao) declare that they have no conflict of interest in submitting this manuscript.

Ethical standards statement

The nature of the study is a retrospective investigation of pediatric forearm bone fractures. Statement of informed consent was not applicable since radiographic images were already generated and were provided for the study by removing identities and remaining age and diagnosis only. All authors have been CITI (collaborative institutional training initiative) certified regardless they worked on programming only, tested the program, or accessed non-identity radiographic images.

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