Chapter 6

Scoliosis Classification

Scoliosis classification scheme is useful for guiding the treatment and testing the clinical outcome [80]. State-of-the-art classification procedures are inherently unreliable and non-reproducible due to technical and human judgmental error while identifying the anatomical parameters [81]. This chapter proposes an automatic classification method that extracts the anatomical features using image processing and applies classification procedures using computerized algorithm. The reliability and reproducibility of the proposed computerized image understanding method are analyzed and compared with manual and computerized method using Kappa values.

6.1 Introduction

During diagnosis of scoliosis, it is often confusing to define the degree of curve. To avoid such confusion and improve the reliability and reproducibility, a classification procedure has been adopted by SRS [82][83].

Scoliotic curve pattern classification that relies on radiographic measures are used in surgical planning [28]. The curves are counted and classified into single, double and triple curves based on the apex number. Classification used to guide the management of scoliosis should be reliable and each classification
Scoliosis Classification

Surgical intervention is generally required, if spinal deformities are severe or progressive. For a single curve such as thoracic, thoraco-lumbar or lumbar curve, there are few differences in the selection of fusion level among different spinal surgeons except for surgical approaches [4]. Inadequate fusion in these curves may result in postoperative curvature deteriorations, trunk decomposition or can produce new deformity. The selection of approach and fusion level should be based on the inherent characteristics of the different curves. A good classification system has to include different types of the curves and should be a guide for surgical planning [84].

There are currently two recognized classification methods, viz., King Classification [4] and Lenke classification [3]. King classification has 5 patterns and Lenke has 42 potential patterns. The King classification method helps in decision for the level of fusion and instrumentation on the spine of the scoliosis patient [4].

The classification by King is still the most widely used technique in surgical planning. It defines 5 thoracic curve types and an identical group called miscellaneous. The King classification relies on subjective identification and measurement of radiographic features including the apical and end vertebrae of the curve, vertebral endplate and origin of alignment of the CSL. The King’s classification is defined as follows (refer Figure 6.1).

- King Type I: Shows an S-shaped curve crossing the midline of the thoracic and lumbar curves. The lumbar curve is larger and more rigid than the thoracic curve.

- King Type II: Shows an S-shaped curve where both the thoracic major curve and the lumbar minor curve cross over the midline. The thoracic curve is larger.

- King Type III: Shows a thoracic curve where the lumbar curve does not
King Type IV: Shows a long thoracic curve where the 5th lumbar vertebra is centered over the sacrum, but the 4th lumbar vertebra is already angled in the direction of the curve.

King Type V: Shows a thoracic double curve where the 1st thoracic vertebra angles into the convexity of the upper curve.

State-of-the-art systems for scoliosis classification can be broadly divided into manual [4] and computerized technique [6], [3], [30]. Manual measurement used in classification procedure includes Cobb angle, curve endpoint, range of lateral bending and vertebral tilt. In computerized classification procedure, the observer need not to be coached or trained where as they have to mark the vertebral body and CSL. It needs a total of 70 landmarks on each radiograph using custom software. In case of manual method, the parameters are manually estimated by observation and angle is calculated using ruler and pencil procedure. Each reviewer is provided with diagrammatic summary of the five types of curves according to the classification system. The position of the certain vertebrae relative to plumb line and whether the lumbar curve and thoracic curves crossed the midline are to be identified manually. The tilt
Figure 6.2: Rule based algorithm for King’s classification [6]
of L4 and T1 and the elevation of the first rib and flexibility index are found using manual intervention.

In case of computerized method, digitized landmarks used are the four corners of the each vertebra from T1 to L5 and two symmetric landmarks on the proximal sacrum. The computerized method adopts the following procedure relating to the PA radiograph. The midpoint between the symmetric digitized points on the sacrum define the origin of the patient XY system. The CSL is defined as the vertical line passing through the origin. Centroid of the vertebral column describes the medial axis. The classification is based on the displacements between medial axis and the CSL with the assistance of computer.

State-of-the-art classification systems rely on subjective identification and measurement of the radiographic features. It also requires individual interpretation and memorizing of the classification criteria. The computerized method’s reliability is influenced by the experience of individual who is using the software tool, severity of scoliosis and quality of image. From the literature it is observed that the classification is unreliable when a radiographic measurement is close to the threshold value used to distinguish between curves of two different types.

The literature review in Section 2.6.3 concludes that even manual and computerized classification system depends on quality of the radiograph, severity of scoliosis and individual experience. There is a requirement of automated system which uses computerized image understanding with automatic identification of number of curves, curvature parameter and required vertebral end-plate identification. The following section describes an automated approach for identification of these parameters using image processing algorithms.
6.2 Automatic scoliosis classification

The inter- and intra- observer variation involved in classification of scoliosis can be completely eliminated by automatic identification of required anatomical parameters in the noisy radiograph. The parameters are number of curves, starting and ending point and steepness of the curves. This automation completely depends on the available spine boundary. Extracting the spine boundary from noisy radiograph is not a direct procedure, need to apply various image processing techniques.

The proposed method depends on the image content to define the envelope containing the ROI. Once the ROI with extraneous information (like rib-cage or abdominal region) is obtained, the row-wise gray profiles are subjected to interpolation using fast fourier transform (FFT) method in order to approximate the data points. This is desirable because after adding its shifted version to the noisy curve, a narrow banded portion of the curve belonging to the mid-portion of the original gray level profile is obtained, which partially suppresses the extraneous details. A final global threshold localized to each row is applied to get an optimized extraction of ROI.

The input image $f(x, y)$ is subjected to a preprocessing which aims at minimizing the extraneous content (rib-cage or abdominal pixels) in the image. The input scoliotic image is added to its up-down flipped version $f(x, -y)$. The maximum gray level in the resulting image is chosen as the first global threshold to remove (dark pixels) all the other pixels having intensity value not equal to the global threshold. As a result, a black and white image, $g'(x, y)$, is defined with the white pixel region enveloping a minimal extraneous content. To retrieve back the original radiograph features localized to the enveloping region $h(x, y)$, perform a bitwise ‘AND’ operation of the region with the image $f(x, y)$. After the preprocessing, the algorithm 2 minimize or completely remove the unwanted region.
Figure 6.4 shows the different imaging techniques used in extracting vertebral column from a given radiographs. The first pre-processing step is to add the original image Figure 6.4a with its up-down flipped version Figure 6.4b, which results in an image shown in Figure 6.4c. The maximum gray level value is chosen as the first global threshold value. The resultant image will be a binary image with white pixel region enveloping a minimal extraneous content as shown in Figure 6.4d. A bitwise logical AND operation has been applied to retrieve back the original X-ray features localized to the enveloping region as shown in Figure 6.4e.

The block matrix-to-row converter is used to extract the $M$ rows of $h(x, y)$. From graphical observation of the matrix obtained after preprocessing, one can infer that the row-wise gray level profiles have noisy components accompanying the gray levels of the ROI. These noisy components (specifically the extraneous information as in the presence of rib-cage, abdominal region or pepper like noise due to poor illumination) are abrupt or spike-like in nature which makes the gray level thresholding on row-wise profiles cumbersome. Generally, the desired ROI lies within the central range of pixels along every row. A solution for providing an improvement in selection of a global threshold value is to smoothen out the spikes or reduce the gray levels corresponding to the noise indices in the row array. Prior to the application of the threshold the spike effects have a smooth gray-level variation along the row array. The threshold value can be aptly set with a successful exclusion of the extraneous information.

A strategy for partially suppressing the unnecessary side information is to employ a method of interpolating the row-wise gray level profiles using FFT (Algorithm 3) method and adding up the interpolated data points to the original data points (row gray profiles). The Row Modulator Block accomplishes the above explained task. There are $M$ such row modulators corresponding to the $i^{th}$ row where $i = 1, 2, \ldots, M$. At last, the modulated rows form the rows of the desired ROI. The FFT based interpolation is independent of sample
data. Hence resultant gray level profiles are subjected to FFT interpolation technique.

Figure 6.5 graph shows the comparison between gray level profiles extracted from the intermediate image $h(x, y)$ and its interpolated one. Figure 6.6 graph shows the partial suppression of the extraneous information by adding the original row level profiles with the interpolated version. Now a threshold value can be directly set without extraneous information as shown in Figure 6.7 graph. This thresholding technique gives ROI as shown in Figure 6.4(f). The complete removal of extraneous information by applying interpolated FFT method is quite robust and gives accurate result.

**Figure 6.3: Block diagram of the extraction of vertebral column**

**Medial Axis and CSL:**
Judgments about classification into 5 different types are based on the deviation of the MA from the CSL and other aspect such as existence of double thoracic and single thoracic curves on the same or different side. Segmentation procedure results with extraction of the vertebral column as shown in Figure
Figure 6.4: Extraction of vertebral column (a) Input image (b) Flipped version of input image (c) Image after arithmetic addition operation (d) Image after thresholding (e) Image after logical AND operation (f) Extracted ROI
**Algorithm 2** To extract ROI from the noisy radiograph

1: Read a gray scale X-ray image $f(x, y)$ of size $M \times N$

2: Add the original image to its flipped version $g(x, y) = f(x, y) + f(x, -y)$

3: Obtain the maximum intensity value of $g(x, y)$ and make all the intensities black which are not equal to the maximum intensity of $g(x, y)$. Let the resulting image be $g'(x, y)$.

4: Perform $h(x, y) = g'(x, y) \text{AND} f(x, y)$

5: Store the gray level profile of $i$th row in an array $a(i)$.

6: Interpolate the intensities by using the FFT method.

7: Store the interpolated values in $b(i)$.

8: Let $c(i) = a(i) + b(i)$

9: Let $G = \max((c(i)) - LT H$, where $LT H$ is the value to be chosen by the user (which would act as global threshold for all the row wise gray level profiles).

10: Make $h(x(i), y) = 0$ for intensities less than $G$.

11: Perform the above operations on all the rows i.e., for $i = 1: M$. The resulting image $h''(x, y)$ is the desired segmented image.

**Algorithm 3** Interpolation using FFT

1: Let $x(n)$: sample data of length $N$, $X(m)$: $N$ point DFT, $P$: re sampling multiplier

2: $L = p \ast (N - 1)$

3: if $(m = 0 \ldots \text{round}(N/2) - 1)$ then

4: $Y(m) = X(m)$

5: else

6: if $(m = N/2)$ then

7: $Y(m) = 0.5 \times X(m)$

8: else

9: $Y(m) = 0$

10: end if

11: end if

12: Compute inverse FFT
Figure 6.5: Original gray level profile with its interpolated version

Figure 6.6: Partial suppression by adding original with interpolation

Figure 6.7: Desired ROI’s gray level profiles
6.2(f). A boundary operation is performed on the extracted vertebral column using erosion technique. The boundary representation consists of pair of co-ordinates. Subsequently extract the MA from these boundary co-ordinates. For every co-ordinates there exists two x-values. The average of these two x-vales will be the x-coordinates of the medial axis. CSL is a vertical line representing the global axis, and it is drawn from the center of the upper endplate of L5.

The MA and CSL obtained acts as an input to the rule based classification algorithm as shown in Figure 6.8. It finds the deviation between the MA and CSL. This deviation is used to identify the category of classification. The rule applied is as follows: if the MA crosses the CSL twice, it is categorized as category-1 otherwise category-2. The category-1 consists of Type-I and Type-II and category-2 consists of Type-III, Type-IV and Type-V. In category-1, if the first level deviation is more than the second level, then it is categorized into Type-I otherwise Type-II as shown in Figure 6.8. Under category-2, if the centroid of the MA has the maximum deviation, then it is classified as Type-
V with one curve with maximum deviation at the center. If the medial axis crosses the CSL once without having the maximum deviation at the center along with the upper region MA and CSL are parallel then categorized into Type-III otherwise Type-IV.

6.3 Results and Discussions

![Figure 6.9: Type-I (a) Input radiograph (b) Segmented vertebral column (c) Extracted boundary (d) Classified as Type-I](image)

Figure 6.9: Type-I (a) Input radiograph (b) Segmented vertebral column (c) Extracted boundary (d) Classified as Type-I
Radiographic features used for classification of scoliosis are MA and CSL. MA and CSL are embedded within the vertebral column. Different thresholding techniques are applied to select proper ROI with only vertebral column from the PA radiograph. The resultant vertebral columns are shown in Figure 6.9(b) to 6.12(b). Determination of spine axis needs only the boundary coordinates. These boundary coordinates are retained using boundary descriptors.
Figure 6.11: Type-III (a) Input radiograph (b) Segmented vertebral column (c) Extracted boundary (d) Classified as Type-III
Figure 6.12: Type-V (a) Input radiograph (b) Segmented vertebral column (c) Extracted boundary (d) Classified as Type-V
Table 6.1: Performance evaluation of the proposed classification system

<table>
<thead>
<tr>
<th>Type</th>
<th>Manual Consistency %</th>
<th>Manual Kappa value</th>
<th>Computerized Consistency %</th>
<th>Computerized Kappa value</th>
<th>Comp. image understanding Consistency %</th>
<th>Comp. image understanding Kappa value</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>67</td>
<td>0.63</td>
<td>75</td>
<td>0.72</td>
<td>93</td>
<td>0.89</td>
</tr>
<tr>
<td>II</td>
<td>62</td>
<td>0.63</td>
<td>81</td>
<td>0.79</td>
<td>95</td>
<td>0.87</td>
</tr>
<tr>
<td>III</td>
<td>68</td>
<td>0.64</td>
<td>78</td>
<td>0.74</td>
<td>91</td>
<td>0.84</td>
</tr>
<tr>
<td>IV</td>
<td>56</td>
<td>0.60</td>
<td>75</td>
<td>0.70</td>
<td>94</td>
<td>0.89</td>
</tr>
<tr>
<td>V</td>
<td>58</td>
<td>0.61</td>
<td>69</td>
<td>0.67</td>
<td>93</td>
<td>0.89</td>
</tr>
</tbody>
</table>

as shown in Figure 6.9(c) to 6.12(c). Coordinates of the MA are nothing but the average coordinates of the boundary in x-axis. CSL is nothing but the vertical line drawn from the center point of the L5 vertebra. Figure 6.9(d) to 6.12(d) shows the MA and CSL for the classification procedure.

Table 6.1 represents the consistency ratio and its corresponding Kappa value for different classification procedures (manual, computerized and computerized image understanding). The consistency is very poor in the manual method compared to computerized and computerized image understanding.

The manual classification procedure, needs each examiner to remember the classification definition by King and he has to find the required parameters as mentioned in the requirements. If the examiner fails in defining the MA and CSL, that error will propagate to classification procedure. Other indexing parameter also depends on the landmark identification procedure. Landmark identification on radiograph is a tedious process, also varies from one observer to other and time. Hence the consistency is very poor with low Kappa values.

The computerized method depends on 70 manually identified landmarks. The consistency ratio is in the reliable range. Here all the landmark identification needs human intervention, remaining steps follows computerized methods.
The Kappa statistics for this methodology is in the substantial range of (0.7).

Computerized image understanding system, first extracts the features as required for the manual and computerized technique by the examiner. The required landmarks are automatically (coordinates points for MA and CSL) recorded as its coordinates points. The classification procedure needs number of curves and its deviation at different stage. That is quantified through the displacement of the MA from its CSL. This will categorize the radiograph into different types as per the King’s definition.

For the moderate curve range, the consistency ratio and Kappa value both are in good range. As a special case curve with more severity (>50), the defined Gaussian filter for the ROI selection may not work with full accuracy, under such situation one may have to increase the filter range. This increase in the filter range highlights unwanted region such as rib cabs and pelvic region. Removal of noise may work up to some extent not of the required level.

The empirical evaluation of the reliability of a scheme by empirical studies of inter- and intra- observer variability quantified by the Kappa statistic produce different findings depending on which specific patients to evaluate the reliability. Among the patients whose radiograph is tested in the present study, there were several for whom the classification, position of a lumbar apex relative to the CSL and location of a curve apex. The proposed system shows better classification consistency compared to manual and computerized. In the proposed work the observer doesn’t require any training in the classification procedure. Still there is some consistency deficiency due to presence of noise in the radiograph. During the extraction of the vertebral column due to noisy nature one may have to select higher value for the Gaussian filter. This higher value leads to more extraneous information in the selected ROI. This minor error may cause misclassification, but works well compared to the existing system.
6.4 Summary

The main source of variability in classification of scoliosis radiograph is the variable landmark identification by the observer. The classification that uses computerized algorithm also needs manual landmark identification. This chapter proposed a unique system for classification of scoliotic radiograph using extracted image features by advanced image processing techniques. The proposed system extracts the vertebral column by gray level profiles. Later segmented vertebral column boundaries are retained using block erosion and enhancement method. The midpoint of these boundary coordinates represents the spine axis. The crossing of spine axis with its CSL will classify radiograph into one among five different categories as per King’s definition. The reliability and reproducibility of the proposed system is not compromised.