Automatic Landmark Detection through Circular Hough Transform in Cephalometric X-rays

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Abstract

In this paper, a knowledge based framework is proposed to detect automatically cephalometric landmarks: Porion (Po), Sella (S), Menton (Me), Pogonion (Pg) and Gnathion (Gn). In this way anomalies can be diagnosed easily by orthodontists. Our framework comprise of two main steps: (1) Adaptive Histogram Equalisation (AHE) is applied to clarify the image which is used to determine the method of treatment in orthodontics and obtained from the plain X-ray. (2) Circular Hough Transform method is used to locate the cephalometric landmarks automatically on the processed image, the method was tested on 7 cephalometric images and our framework accurately and automatically locates these 5 cephalometric landmarks.

1. Introduction

The development of radiographic method provided orthodontists to diagnose the orthodontic disorders and to locate the significant anatomic landmarks on the human head. However, the cephalometric evaluations are carried out by measurement of distances, angles and ratios through the formation of planes by using these landmarks. Later, based on these evaluations, an orthodontist diagnoses anomalies, decides the treatment plan and estimates future relationships. Thus, the accuracy of the cephalometric landmarks identification is crucial [1]. Moreover, an orthodontist is able to reach quantitative observation-based objective results rather than biased assessments.

Therefore, many researchers investigate new solutions to automate the cephalometric analysis, namely, to develop a framework that takes a particular patient's lateral head radiograph and provides all the information an orthodontist with the high accuracy of landmark identification. Currently, manual cephalometric analysis is the most widely used compared to the computer aided approaches. In both, a clinician identifies the location of the cephalometric landmarks.

The first study regarding the automatic detection of cephalometric landmarks dates back to 1986 by Levy-Mandel et al [2]. A knowledge based framework is offered in the paper. The algorithm starts with filtering step for noise reduction and image enhancement. In this step median filter, the histogram equalisation process and the sharpening filter applied to the image. After that edge detection with Mero-Vassy operator is used. Finally, a line-following algorithm is applied to the system with a predefined sets of rules and a simple interpreter. The algorithm aims to extract only significant lines not the positions of the landmarks. The algorithm was applied to x-rays and 23 out of 36 landmarks detected. Parthasarathy et al. [3] suggested the image pyramid method based on Levy-Mandel to reduce processing time. Similar to Levy-Mandel, median filter is used for preliminary filtering, histogram equalisation for improving the contrast but different gradient operators are used to improve edges. In this way, they aim not only to extract the significant lines but also to identify the location of the landmarks. Proposed method was tested and out of 9 landmarks, 18% was detected with an error below 1 mm, 58% below 2 mm and 100% below 5 mm. Cardillo and Ahmed [4] used the pattern-matching techniques based on gray-scale mathematical morphology for identifying landmarks. The system was trained to find 20 landmarks. The algorithm ran on 40 x-ray images, 85% rate of recognition was achieved. In other study about automatic landmark detection [5], mathematical morphology techniques-based pattern detection algorithms are used. The systems detected 17 landmarks on 20 images, and have a success rate over 90%. In the study of El-Feghi et al [6], neuro-fuzzy system and template matching methods are used. The system is trained for 20 cephalometric landmarks on 565 cephalogram images in the database, and preliminary results show that the rate of perception is more than 90%. Rahele Kafieh et al. [7] used Susan Edge Detector, ASM and template matching methods for detecting landmarks. Cellular Neural Networks are used in [8] and 10 landmarks are detected on 41 x-ray images. In the study by S.Shahidi et al [9], 16 landmarks were selected for detection. They used template matching and edge enhancement methods and identified 12.5% of landmarks with the mean error below 1 mm, 43.75% below 2 mm. The mean error of all cephalometric landmarks excluding Anterior Nasal Spine was below 4 mm.

Many new state-of-the-art methods have been proposed in recent years. Claudia Lindner et al [10]. have developed fully automatic system (FALA) for finding cephalometric landmarks. In the system, the researchers applied Random Forest Regression-voting to detect the position, scale and orientation of the skull. This process makes the framework robust to any variations in image acquisitions. After that Constrained Local Model (RFRV – CLM) is used to locate landmarks. The framework achieved 84.7% of landmark localisation within the clinically accepted precision range of 2.0mm. To need to overcome the limitations of the problem, three dimensional surface models have been often used [11-14]. Marina Codari et al [11] developed a semiautomatic computer-aided cephalometric landmark annotation for Cone Beam Computerized Tomography. The framework is based on 3D cephalometric analysis that estimates the three dimensional positions of 21 cephalometric landmarks. Adaptive cluster-based segmentation of bone tissues is applied followed by an intensity based registration of an annotated reference volume. Experimental results show that annotation error was less than 5.00 mm for 90 % of landmarks and less than 2.50 mm for 63 % of them.

The remaining part of this study is shaped as follows: the material and method to be used by us during the study is explained in chapter 2. The practice is mentioned in chapter 3, while the results are mentioned and assessed in chapter 4.

2. Material and Method

2.1. Adaptive Histogram Equalisation

Histogram equalisation process is a frequently used technique to improve a bad-quality image. The purpose is to make the histogram of the image as flat as possible. The histogram equalisation process consists of the following four steps:

1 – The histogram of the image is found (pixel number graphic for each gray level)

2 - Cumulative histogram values are found by using the histogram. Cumulative histogram value is a magnitude consisting of the values obtained through the addition of each value of histogram itself with those before them.

3 - Cumulative histogram values are normalized (divided by the total number of pixels), and multiplied by maximum color values demanded to be available on the new image, the outcome is rounded down to zero. Therefore, new gray level values are obtained.

4 - Values found on the 3rd step are assigned to pixel values in a way they are exactly correspond, and a new histogram graphic is drawn.

$$S_k = \sum_{j=0}^{k} \frac{n_j}{n} * (L-1) \quad k = 0,1,2,\cdots,L-1 \tag{1}$$

where n is the number pixels in the image, n_j is the number of pixels having gray level j , L is the number of possible gray levels and S_k is the discrete cumulative distribution function of the new image.

On the other hand, the adaptive histogram equalisation is used to improve image contrast on the local data. The image is divided into rectangular sections having a grid shape, and ordinary histogram equalisation process is applied to each section. Depending on the image the size and number of sections varies to obtain the best result. The method improves the local contrast.

(a) (b)

Fig. 1. a) Original Image b) Adaptive Histogram Equalisation

2.2. Circular Hough Transform

Hough transform works with a logic of edge pixels polling the possible geometrical figures. Detection of the figure or landmark through the use of Hough transform is carried out by the following steps:

1 - Edges are determined by edge extraction method on the source image.

2 - The image is converted into dual status (black-white).

3 - Each edge pixel is enabled to poll the possible figures on an accumulator matrix.

4 - Due to the fact that the figures with high accumulator values are those receiving the highest votes, their possibility of being on the image or being clear is the highest.

5 - The figures found can be printed on the image arbitrarily.

In Circular Hough Transform, the accumulator matrix consists of 3 dimensions. They are $[a,b]$ landmarks, the coordinates of the center of the circular region, and r landmark, the radius. The center of the circular region can be found by using the mathematical equations:

$$R^2 = (x-a)^2 + (y-b)^2 \tag{2}$$

$$x = a + r\sin(\theta) \tag{3}$$

$$y = b + r\cos(\theta) \tag{4}$$

3. Application

This section explains the implementation issues and demonstrates simulation results. We implement our algorithm with Matlab version 8.3.0.532 (R2014a) and use a portable personal computer with Intel Core i5-2430M CPU 2.40 GHz processor and 4 GB Ram. To produce input cephalometric radiographs, image Kodak CS 9000 X-ray unit is used. The size of image is 1920 x 1440 pixels and its resolution is 96 dpi.

We implemented a general Matlab GUI interface to run various image processing algorithms on a cephalometric x-ray so that we are able to compare their performance. In this paper we only present some simulation results.

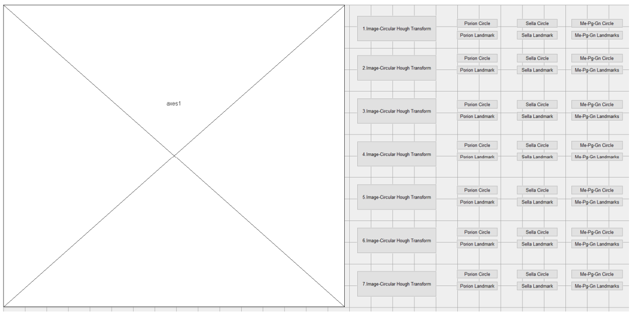


Fig. 2. GUI interface of the application

In the first step of our algorithm, input image is improved through the adaptive histogram equalisation method. Then, the circular Hough transform is applied to the improved image. As a result, the circular regions with the radius ranges from 19 to 26 pixels are detected and the meaningful ones are numbered. The resulted image is shown in Fig. 3.

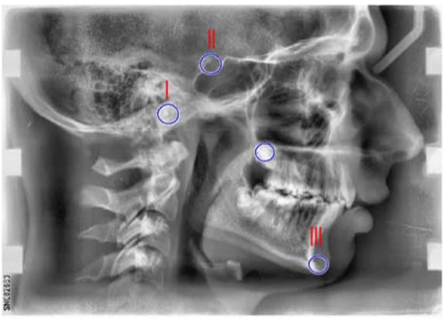


Fig. 3. Circumferential areas detected, having similar radius.

Detailed analysis with the orthodontist states that the landmark Porion (Po) lies on the circumference the circle numbered I, the landmark Sella (S) is inside the circle numbered II and the landmarks Menton (Me), Pogonion (Pg) and Gnathion (Gn) lie on the below arc of the circle numbered III. The remaining circular region is determined by circular Hough transform but it doesn't have any meaning for our purposes.

Later, to determine the coordinates of the central point of the each circular regions, a rectangular area containing corresponding circular region is determined (see Fig. 4. the rectangle containing the circular region numbered I) .

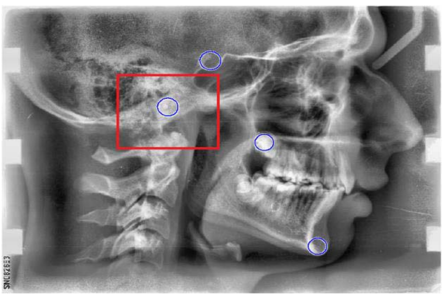


Fig. 4. The area required to be scanned for Circular Hough Transform

To reassure the location of the circular region numbered I we apply the circular Hough transform to the section of the image covered by the rectangle. Fig. 5 shows the result.

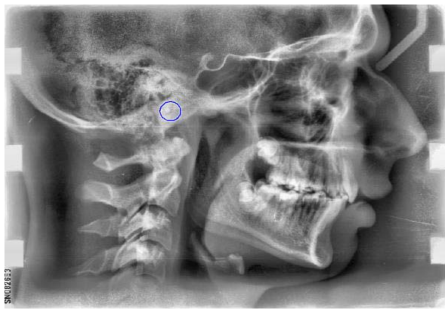


Fig. 5. Circumferential Area Detection

Then the coordinates of the center of the circular region in are identified. The problem remains to identify the position of the landmark Po.

Fig. 6. shows the position of Po at the end of whole process.

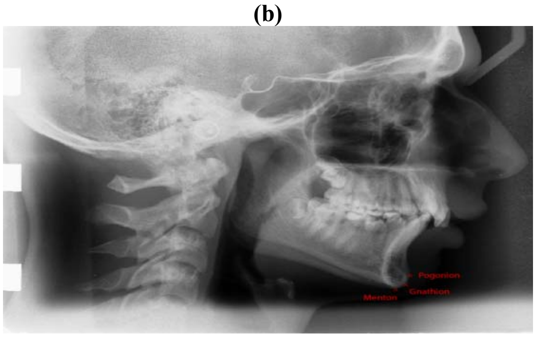
Fig. 6. Marking on the Circumferential Area Found

The process starting from selecting rectangular region to obtaining the position of the corresponding cephalometric landmark is repeated for each numbered circular regions in Fig. 3.

Our framework was tested seven different lateral cephalometric images. In each case, Po, Me, Pg and Gn lie on the arc of the circular region but S is inside the circular region. Fig. 7 shows the positions of these five cephalometric landmarks.

(a)

(b)



(c)

Fig.7. a) Porion Landmark, b) Sella Landmark, c) Menton, Pogonion and Gnathion landmarks

The block diagram of our framework is shown in Fig. 8.

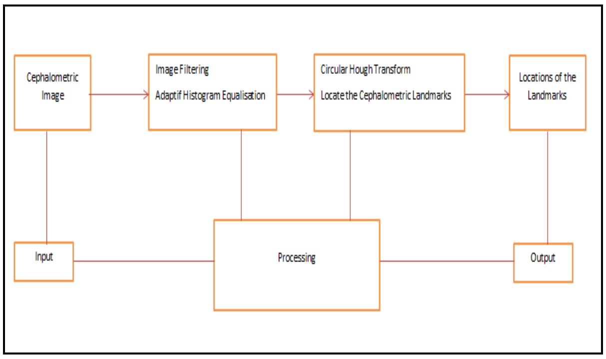


Fig.8. The Block Diagram of Proposed System

4. Conclusions

This paper presents the knowledge based cephalometric landmarks detection method. The framework takes the lateral cephalometric image as input and returns the lateral cephalometric image with landmarks as output. As shown in Fig. 8, there are basically two main steps in the algorithm: filtering step, identifying step. We tested the algorithm 7 cephalometric lateral radiographs. The framework detected the five cephalometric landmarks within one millimeter error compared to an expert orthodontists manually identified. The experimental results indicate that the framework is robust and efficient for landmark detection.

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5. References

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