CHAPTER 1

INTRODUCTION

1.1. Background

Cephalometry is the scientific study of the measurement of the skull. Various measurements composed of a series of angular and linear measurements are made using specific reference points called landmarks. The analysis of these measurements is performed by the orthodontist. The measurements help in the assessment of the facial skeleton, the teeth and soft tissue profile for the diagnosis of anomalies, their treatment planning and monitoring, and the evaluation of final treatment outcomes.

Radiography as a diagnostic tool in orthodontics was introduced by W.A Price in 1900. Broadbent's cephalometer opened the door to Brodie's landmark growth studies and Down's cephalometric analysis. Today cephalometric radiography is a method, which has innumerable practical applications for the orthodontists and plastic surgeons. The head positioning cephalostat allowed lateral skull radiographs to be obtained in a standardized manner. In turn this standardization of radiographic projections allowed the exact measurement and comparison of oral and craniofacial structures either directly on the radiograph or through superimposed tracings of landmarks obtained from the radiograph. The lateral cephalometric radiograph shown in Fig 1.1 displays numerous cranial, facial and oral anatomic structures imaged from the lateral aspect. Thus, these radiographs have become virtually indispensable to orthodontists in the treatment of patients [1-3]. The diagnostic value of cephalometric analysis depends on the accurate and reproducible identification of clearly defined landmarks on cephalometric radiographs. Different analysis use different landmarks Fig 1.2 shows some landmarks.

Figure 1.1: Digital lateral cephalogram.

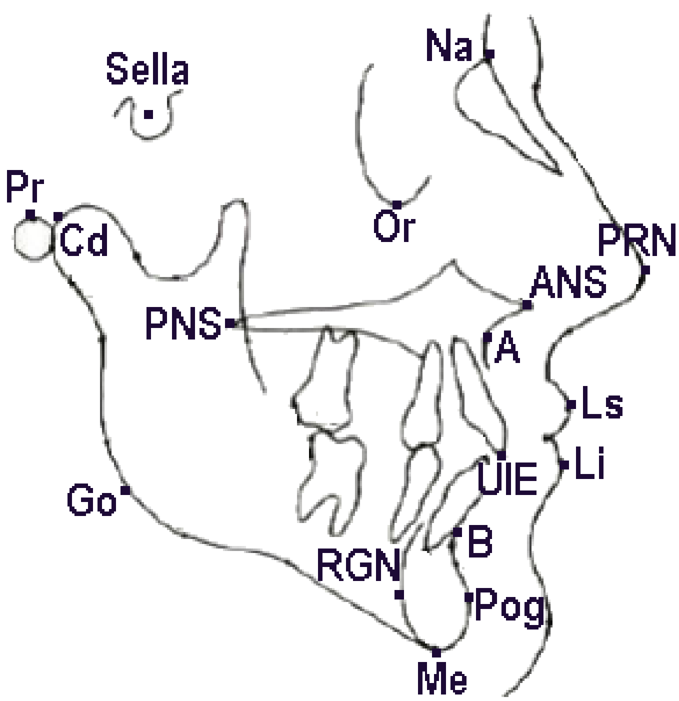

Figure 1.2: Tracing with some hard and soft tissue landmarks.

In orthodontics, many of the landmarks have been defined but only around 30 landmarks defined by Rakosi [3] are commonly used. The actual selection of landmarks that are used for the cephalometric analysis depends on the measurement standard used and on the personal preference and experience of each orthodontist. Downs analysis stimulated several enthusiastic investigators to evolve their analysis. A large number of analyses that followed only confused the issue for the orthodontist. Simply too many landmarks were identified, and many measurements were advocated. As a result meaningful information was submerged in much of inconsequential details. Steiner selected the most significant parameters and evolved a composite analysis, which he believed would provide the maximum clinical information with the lowest number of measurements [1].

Several other standards for measurements in the cephalometric analysis like Rickett's analysis, Wit's appraisal and McNamara analysis are proposed in literature. Steiner analysis is the standard technique for cephalometry in India. The landmarks differ depending on their type (soft tissue landmarks or hard tissue landmarks lying on the bony structure). Another criterion to classify landmarks is their location (landmarks lying on contour turning points both convex and concave, on centre points of regions and between soft and hard tissue profile) [1].

Generally, in clinical diagnosis, different doctors cannot get same position for certain landmarks. An error of ±2 mm in landmark placement has been suggested as acceptable limit [1-3]. Three studies specify three different acceptable levels of error. In a study conducted using 33 landmarks by Miethke (1989) [1] for manually marked landmarks, a variability of ±2 mm was observed in most of the landmarks. Out of the 33 landmarks 25% showed a variation of more than 2 mm. From the results, it was concluded that some landmarks were localized more exactly by the observers than the other landmarks. The acceptable mean location error (ME) derived through this study is ±2 mm. In another study, Trpkova et al. [4] recommend a total ME of 0.59 mm for the x coordinates and 0.56 mm for the y coordinates. Thus according to them the acceptable level of error is 0.81 mm. However, their results are based on Meta analysis performed on six studies from 1966 and 1987 with four to ten landmarks. The authors have used 15 landmarks in their analysis. Meta analysis is commonly used statistical techniques to integrate the results of various studies. Even so, the analysis is not as reliable as a clinical trial using large randomized samples [5]. Another recent study [6] the mean standard error is given equal to ±1.74 mm for 27 landmarks. The authors conducted their study on ten good quality digital cephalograms on, which landmarks were digitally identified by 27 observers. Their results are more similar to Meithke's study than the acceptable limit proposed by Trpkova. Thus, considering Miethke's study a landmark detected within a range of ±2 mm is considered accurately detected. This is the acceptable limit used in most automatic cephalometric landmark detection studies.

Landmarks are usually marked manually by tracing using conventional light box and an acetate tracing paper using a pencil. This process is very monotonous and time consuming. Another way is to directly mark landmarks on digital cephalograms on the screen. Generally, in clinical diagnosis different doctors cannot get identical position for particular landmarks, results vary from one doctor to other (various doctors cannot get the same position for certain landmarks). At times, there is an error, though the landmarks are located by the same medical doctor at two distinct times. Time pressures can further contribute to decreased reliability when the clinician is asked to subjectively define the positions of a series of cephalometric landmarks.

The principal reasons for difficulty in identifying the landmarks are the poor diagnostic quality of a cephalometric radiograph, large variations in biological features of the patient's skull structure (hard and soft tissues), overlapping structures, abnormalities and areas with subtle changes in grayscale. To identify the landmarks the dentists have to use their training and expertise gained through several years of clinical practice. It will considerably increase the efficiency of orthodontists if the landmark location operation could be performed automatically using a personal computer rather than manually. Such a system will reduce the subjectivity involved due to intra and inter examiner variability and save valuable clinical time. Automatic cephalometric landmark detection has been a subject of research for more than 25 years and attempts to automate the localization of landmarks has been attempted by many researchers with varying degree of success. More sophisticated techniques are still required to improve the accuracy of the results.

1.2. Framework for Automatic Landmark Detection

Initially, the researchers employed image enhancement and edge detection and tracking techniques to localize the landmarks. These systems could merely locate landmarks near or on the edges. Owing to low contrast, complex structure and blurry nature of X-rays, it is difficult to always extract accurate edges, and thus the detection of some landmarks may have poor location accuracy.

To overcome these problems some researchers worked on gray scale appearance around each landmark using deformable models. In model-based technique's location of landmarks is found by deforming the model then search is made around the current position of each landmark using a model of image texture in small regions covered by the model. Active shape model is one such model. However, the performance of these models is often limited by their inability to capture the full range of biological shape variability due to, which they are not able to follow the finer details of a shape. These models may be used to find the approximate the initial landmark locations.

An alternate strategy is based on pattern matching. A majority of these methods use a local search window to find the true location of landmarks by applying local template matching. Local template matching avoids false detection due to presence of similar structures nearby and reduces the computation time. The variability of some landmarks is high, which is difficult to capture in a single template. Thus multiple templates are used to find each landmark. Most of the techniques based on pattern matching try to optimize the results by combining the following steps:

i. Image preprocessing to improve the contrast, enhance the edges and suppress the noise.
ii. In the next step a local search area is found for each landmark by using techniques like ASM, neural networks or dividing the images using the prior anatomical knowledge.
iii. The landmarks are finally, found using local template matching.

In the proposed framework, robust global features are used to find approximate landmark locations that help in locating local search windows. In the next step, local template matching is applied using coarse to fine strategy.

1.3. Survey and Review of Related Literature

For automatic landmark localization, initially the researchers focused on knowledge based systems. Through these systems, they tried to emulate the procedure followed by the orthodontist. Prior to 1990, the focus was to locate landmarks using image processing techniques together with prior knowledge of the cranial structure. One of the earliest works in automating the landmark detection was published by Levy-

Mandel et al. [7]. They used a knowledge based line extraction technique to track landmarks on well defined outlines. They begin by first preprocessing the digital X-ray image using histogram equalization and median filtering to enhance image contrast and remove the noise present in the image. An edge detecting operator was used to enhance edges, and the significant edges were then extracted in a predetermined order using a-priori knowledge of the typical shapes of all relevant edges. For each of the specific structures, an algorithm was encoded and thus these algorithms were called hand crafted algorithms. After extracting relevant edges, positions of the landmarks were determined according to a set of predefined geometrical properties of lines, intersections or exterior boundaries. Their system was tested using only two high-quality gray scale cephalometric radiographs of size 256×256 pixels. In their result, they have shown that 23 out of 36 landmarks could be determined on the best-quality cephalograms, but the result is not compared with any standard.

Yan et al. [8] proposed some improvement over [7]. They proposed a more efficient algorithm for the calculation of median filtering and better representation of the knowledge base. Their system uses blackboard architecture and multiple knowledge sources within an integrated model-based system. Parthasarathy et al. [9] presented a similar scheme to [8]. In addition, they propose image pyramid method to improve the efficiency of landmark search. They used median filter for prefiltering, histogram equalization for contrast enhancement and different gradient operators for edge enhancement. For testing they have used five cephalograms of size 480×512 pixels of varying quality and compared the efficiency of their system to the landmarks as placed by two experts. Of the nine landmarks shown in the results about 18 percent were located within 1 mm, 58 percent within 2 mm and 100 percent within 5 mm. Tong et al. [10] presented an extension to the work of Parthasarathy et al. [9]. Their system located 17 new landmarks, not included in their earlier work. They indicated that their results could be combined to yield a full cephalometric analysis, if both systems were used together. Again, five cephalograms were considered for testing of the 26 landmarks 40% was located within 1mm, 70% within 2 mm and 95 within 5 mm.

Forsyth et al. [11] described how handcrafted algorithms could be integrated in black board architecture. They developed a recalling algorithm to locate 19 landmarks. They tested their method on 10 X-ray images of size 512× 512 with 64 grayscales and reported that the errors of 63% points were within 1mm and 70% within 2mm. Cheng et al. [12] in their method divided the image into many subimages. These subimages were then enhanced using an averaging and band reject filter. For some subimages coarse to fine search was performed using the image pyramid. Then the landmarks were extracted by using a combination of elastic method, and direction planned method. Ten pieces of X-ray films were used as samples and 13 landmarks were detected. The average error for 13 landmarks is 1.94 mm.

Ren et al. [13] proposed a new analysis method based on the clinical knowledge for the automatic identification of cephalometric landmarks in digital cephalometric radiographs. In their method after locating landmark regions, the image is enhanced by image layer technique based on multi-level knowledge according to the gray level distribution of the objects and the backgrounds. Next, the image is changed to the binary form for the extraction of edges. The edges are used to trace contour. Based on the clinical knowledge and the features of the landmarks, 43 points are automatically identified. In the experiment conducted on ten sample radiographs with 200 dpi and 1200×1500 sizes, 24 points were automatically detected within 1 mm and 19 points within 0.5 mm.

Handcrafted algorithms can detect landmarks near or on the edges. Such techniques depend on the quality of X-ray expressed in terms of sharpness (related to blurring and contrast) and noise. Contrast and blur are dependent on tissues being examined. Noise is related to radiographic complexity of the region. Owing to low contrast, complex structure and blurry nature of X-rays, the detected edges may suffer from false and missing edges, and their location accuracy may be poor [1-2]. This may affect the overall performance of the algorithms. These techniques could be improved using better image processing techniques. However, there are few more underlying flaws like:

i. The algorithms are limited to a small population of images unless the code is written to handle variations in biological shapes.
ii. The landmarks not on the clear edge are not detected.
iii. Addition of new landmarks is difficult using these techniques.

To overcome these problems some researchers worked on statistical and model-based approaches that used gray scale appearance around each landmark [14-20]. The methods listed in these references use similar approach of generating a model of the gray levels around each point from a training set then matching this model to a new image to locate the points of interest. Rudolph et al. [14] used spectroscopy to characterize the gray level around the landmarks from a training set located by hand. They used images of size 64×64 pixels and could locate all landmarks within 4 mm. Romaniuk et al. [15] in their paper present and compare two methods for statistical localization of partially occulted landmarks. A-priori knowledge is used to train the models unlike that used in [16], which uses manually marked landmarks for training. In this work, models are built with 80 radiographs and tested using 14 landmarks. The first method based on explicit mapping function gives mean error of 2.54 mm and the second method using pseudoinverse and the kernel trick gives an error of 4.6 mm. Hutton et al. [16] first employed active shape models (ASM) for cephalometric landmark detection. A system based on machine learning, and semi-automatic feature identification is developed. The evaluation of the work showed that ASMs did not provide the amount of accuracy required for cephalometric landmark detection, although they provided the room for more flexibility in landmark shapes. The authors proposed a method based on active contours composed of the mean observations, and the variability authorized around the mean. This model is then positioned statistically on an image and is deformed to correspond to the landmark locations. The algorithm was tested on 63 images, and 55% of 16 landmarks were within the range of 2 mm. To overcome the limitations of ASMs like the grayscale appearance is not reproducible across all cephalograms thus limiting the landmark's location accuracy. Yue et al. [17] proposed a modified ASM that improves the accuracy from 51% as achieved by Hutton to 71%. In this method, the authors identify five reference landmarks using edge information and handcrafted algorithms, and another seven landmarks by pattern recognition. A modified ASM is used to find all the feature points using shape partition of the image using the 12 reference landmarks. Some other researchers proposed cephalometric landmark detection approaches based on the active appearance model (AAM) [18-20]. Rueda et al. [18] used AAM and reported an average accuracy of 2.48 mm by using a training set of 96 cephalograms. Vucinic et al. [19] proposed multi-resolution approach to AAM. They achieved an average accuracy of 1.68 mm and reported a success rate of 61% within 2 mm precision. Saad et al. [20] unified AAM and simulated annealing to detect cephalometric landmarks. In the study, 27 pretreated cephalograms of size 794×1042 and 256 gray levels are used (20 for training and 7 for testing). Their results showed a mean error of 3.247 mm for 16 landmarks using AAM and a mean error of 4.081 mm for the same landmarks using ASM. The results showed an improvement of 25% with the use of AAM instead of ASM.

Chakrabartty et al. [21] applied support vector machines (SVM) to model discrimination boundaries between different landmarks and between the background frames. The experiment was conducted using 130 X-ray films of size 700×500 pixels. 70 images were chosen for training, 20 for cross validation experiments and the remaining 40 images were chosen to evaluate the performance of the trained recognizer. Such selections were repeated randomly for ten times, and evaluation results were averaged to obtain final results. The result for eight landmarks showed that for tolerance of 5 mm, the accuracy is 96 percent and for tolerance 1 mm the accuracy is around 94 percent.

Model-based methods are often limited by their inability to capture the full range of biological shape variability when trained on a relatively few sample owing to which they cannot follow the finer details of a shape. This is clearly evident from the results quoted in the papers [16, 17]. Thus, these techniques are more suitable to find a small area where the desired landmark is expected to locate.

An alternate strategy is based on pattern matching. A majority of these methods [22-26] find a localized search window followed by template matching to compute true location of landmarks. Most template matching techniques are applied in a local window to reduce the computation time and reduce false detection of similar structures elsewhere in the image. Cardillo et al. [22] in their work, they have used mathematical modeling to reduce the search area for the landmark then applied template matching techniques based on mathematical morphology to pin point the exact position of the landmarks. The algorithm uses a statistical approach to training to overcome subtle differences in skeletal topographies and decomposition to desensitize the algorithm to size differences. 20 landmarks of varying type were selected for the experiment. The algorithm was tested on 40 randomly selected cephalograms of size 512×490. 85% of the landmark results obtained was within 2 mm. Sanaei et al. [23] use a combination of statistical pattern matching and fuzzy logic to detect landmarks. Quantitative results are not given in the paper. Grau et al. [24] improved Cardillo method by combining a simple knowledge based edge detection step to determine approximate location of significant structures of the image. The results are then used to define a small search area for each landmark. Pattern detection based on mathematical morphology is used to determine the exact location of landmarks. The system has been tested on 17 landmarks using 20 test images. Average error quoted is 1.1 mm. Liu et al. [25] used neural network and genetic algorithm to search for subimages that contained the needed landmarks. However, they do not mention the accuracy of the landmark positions obtained. Eli-Feghi et al. [26] in their work the process of localization of landmarks is carried out in two steps. Firstly, a smaller expectation window is derived for each landmark using a trained neuro-fuzzy system then a template matching algorithm is applied to pin point the exact location of the landmark. The system is trained to locate 20 most commonly used landmarks on a database of 565 images. An average recognition rate of 90 % is quoted in the paper. Kafieh et al. [27] find three reference points using Susan edge detector and knowledge based method and further use ASM [16, 17] with the strategy used in [26].

Template matching techniques may suffer from false detection due to presence of similar structures nearby. The variability of some landmarks is high, which is difficult to capture in few templates. In template matching based on mathematical morphology it is hard to extract structuring elements for all the landmarks and addition of new landmarks is difficult. These methods can be successfully implemented by using local template matching to avoid false detection. Landmark detection can be further improved by using rotation and scale invariant template matching and hierarchal templates.

Few researchers explored soft computing techniques [28-30]. Ciesielski et al. [28] this paper describes genetic programming for craniofacial landmark detection in digital X-rays. The method was tested only on four landmark points. Innes et al. [29] used pulse coupled neural network (PCNN) to highlight regions containing key craniofacial features from digital X-rays. The method uses an averaging filter to minimize noise followed by a PCNN to highlight the features relevant to the detection of the landmark. The output of the PCNN, a binary image, will be used by a subsequent process such as curve following or Hough transforms to identify the position of the cephalometric landmark.

The method was tested on three landmarks. On a test set of 109 images the PCNN could accurately segment regions containing soft tissue and bony structure with a success rate of 93.6% and 88.1% respectively. The PCNN could extract features surrounding $Sella$ point with a success rate of 36.7%. Finding good parameter values automatically for different landmarks is difficult issue in this technique. Leonardi et al. [30] investigated the use of cellular neural networks for the automatic landmark detection.

In soft computing large data set is required to train the system. The training may be slow and each time a new landmark is needed the system needs to be retrained. Large number of parameters needs to be set such as network weights, number of neuron layers, and number of neurons in each layer. It may train or may not train for a specific landmark.

Most recent methods try to optimize the results by combining different techniques [17, 26, and 27]. There are few more techniques proposed in [31-34], but the quoted results are not significant. Comparative analysis of various cephalometric landmark detection techniques is given in Table 1.1.

Table 1.1: Comparison of various landmark detection algorithms.

Year and Author	Algorithm and No. X-ray on which tested	Landmarks Detected	Results	Issues
Parthasarathy et al. [9] 1989	Knowledge based handcrafted algorithm. No. X-ray = 05	09	18%<01mm 58% <02mm ME =2.06	Rigid knowledge base rules thus difficult to add new landmarks and unable to locate non edge landmarks.
Tong et al. [10] 1990	Improved handcrafted algorithm similar to Parthasarathy et al. [2]. No. X-ray = 05	17	76%< 02 mm ME = 1.33	In addition to above problems criteria for success is not specified.
Cardillo et al. [22] 1994	Use local template matching based on mathematical morphology. No. X-ray =40	20	88% <02mm ME =1.1 SD=1.9	Extraction of structuring elements for all the landmarks is not possible.
Forsyth et al. [11] 1996	Uses feature appearance models, blackboard architecture. No. X-ray = 10	19	63% <01mm 78%<02mm	Tested on a small data set. The results may not be statistically accurate.
Rudolph et al. [14] 1998	Pattern matching based on spatial spectroscopy. No. X-ray = 14	15	13%< 02mm ME= 2.07	System which applies only pattern matching may suffer from false detections.
Hutton et al. [16] 1999	Evaluates the use of active shape model for landmark detection. No. X-ray = 63	16	13% < 01mm 35% < 02 mm ME=4.08	Accuracy of results is low, but can be used to provide first estimate of landmarks.

Grau et al. [24] 2001	Uses edge detection and pattern detection technique based on mathematical morphology. No. X-ray = 20	17	88.6% < 02 mm M E = 1.1 mm	Sensitive to noise Only one component used for matching and thus algorithm not desensitized to size difference.
Ciesielski et al. [28] 2003	Genetic programming. No. X-ray = 36	04	85% < 02 mm	Genetic program based techniques consume more time to provide optimal solution.
Chakrabartty et al. [21] 2003	Gini support vector machine in conjunction with projected principal-edge distribution (PPED). No. X-ray = 40	08	93%< 01 mm	Tested only on 08 landmarks.
Romaniuk et al. [15] 2004	Active contours with similarity function. No. X-ray = 40	01	ME= 1.2 mm	Results are insignificant, tested only on one landmark.
El-Feghi et al. [26] 2004	Combines knowledge based method with neuro-fuzzy system and template matching. No. X-ray = 600	20	90% < 02mm	One of the four points used as refer are not present in all lateral cephalograms. Edge based landmark detection is not robust due to blur and low contrast in X-ray image.
Yue et al. [17] 2006	Combining knowledge based method, pattern matching and modified ASM model. No. X-ray = 286	12	71% < 02mm	Finds five reference landmarks using Canny edge detector which is not robust. ASM is not optimal solution for finding exact landmark location.
Kafieh et al. [27] 2008	Find three reference points using Susan edge detectors and knowledge based method and further uses ASM, neural network and template matching. No. X-ray = 63	16	24%< 01mm 61%<02mm	Edge detection is used to find three reference landmarks which are not very robust. Too many adjustable parameters which need to be optimized for good results. Templates are made rotationally invariant by rotating the template. But the structures in the cephalograms are arbitrary rotated so this is not efficient.
Leonardi et al. [30] 2009	Cellular Neural Network. No. X-ray = 41	10	100%<0.59 mm	Control and feedback templates are specific to landmarks. Hard to find them for all landmarks.
Vucinic et al. [19] 2010	Multi-resolution approach to AAM.	17	61%<2mm Mean Error=1.68 mm	Require good initial shape close to the actual landmark positions. The results are also affected due to occlusion and noise.

1.4. Challenges in Automatic Landmark Detection

Locating the landmarks (both on bony structure and soft tissue) on X-ray images is a challenging task since the images lack hard edges, suffer from shadows and noise and outlines are not clearly defined. Some reasons for distortion in cephalograms are given as follows:

i. Cephalograms are 2-D X-rays used to examine the three dimensional structures. This leads to differential projective displacement of anatomical structures lying at different planes within the head.
ii. The objects in the cephalograms are magnified by different amounts owing to divergence of X-ray photons resulting in double edges.
iii. High kilovolt setting of the X-ray gives better density as it can penetrate hard bony structure but low contrast between the bony structure and the soft tissue, whereas low kilovolt setting gives better contrast but low density.
iv. The cephalograms may suffer from image blurring caused by movement of the patient.
v. Furthermore, any X-ray photon whose initial direction is scattered by patient's hard and soft tissues creates image noise.

1.5. Research Objectives

The main aim of this research work is to explore and develop efficient automatic landmark detection algorithms both for soft tissue landmarks and bony structure landmarks. Further, cephalometric X-ray images generally suffer from low SNR, low contrast and noise. Thus, enhancement of these images is important for improving the visibility of details and their quantification. A comprehensive study of various enhancement techniques has been done, to select techniques that are not accompanied by undesirable effects like loss of valuable image information or addition of artifacts. This is very important for cephalometric images as they are used to abstract quantitative data. Keeping these issues in view ,the research work has the following objectives.

i. Study the existing image enhancement methods used in different landmark detection algorithms. Propose an improved enhancement methods for cephalograms to suppress noise and improve contrast without losing or modifying the image information necessary for accurate landmark detection.

ii. Study and implement improved edge detection algorithms and analyze if they can reliably be used to find landmarks on the edges.

iii. Establish and understand the existing automatic cephalometric landmark detection algorithms and propose improved algorithms that are fully automatic to detect both soft tissue and bony structure landmarks with better location accuracy.

1.6. Major Contributions and Achievements

The major contributions of this research work toward improvement in automatic landmark detection and enhancement of cephalometric images are summarized as follows:

i. Two new algorithms for cephalometric X-ray enhancement are proposed. A novel noise suppression method is proposed that has the capability of removing both Poisson's noise and Gaussian noise. The signal to noise ratio of the enhanced images is significantly improved. The images are smoothed while preserving the image details that are important for accurate detection of landmarks. In addition, the technique is faster than other state-of-the-art techniques for noise suppression.

ii. The cephalograms are low contrast. At many locations in the images due to subtle changes in the gray scale values the image details are hardly visible. Most existing techniques for cephalometric enhancement and analysis use traditional histogram equalization technique for improving the contrast but this technique may add artifacts and enhance noise, thereby giving very unnatural looking images. In this work, we propose an effective and efficient contrast enhancement method that greatly improves the visibility of image details without amplifying noise or adding artifacts to the enhanced image. The enhanced images are natural looking and are useful for visual perception and further processing.

iii. Two effective algorithms are proposed for detecting edges in cephalograms. A hybrid algorithm using fuzzy logic and mathematical morphology is proposed. In case of cephalometric images, the method gives better results than Canny and Susan, the two standard techniques for edge detection. In the second method, subpixel level edge detection is proposed using pseudo-Zernike moments. Subpixel level edge detection can be used to improve the location accuracy of detected landmarks.

iv. Two algorithms are proposed for landmark detection that enhances the accuracy of the landmark localization, are robust to image noise and distortions. The main advantages of the first algorithm are:

   a. The proposed algorithm uses Zernike moment features, very good shape descriptors for initial landmark approximation instead of using edge features. In edge detectors due to complexity of structure, low contrast and blur in X-rays, it is difficult to get good edge detection results for all X-ray images. Moreover, each edge detector has certain parameters, which need to be adjusted. The Zernike moments based approach is a non-parametric approach.

   b. The rotation of landmark structures is arbitrary in cephalograms and the templates rotated at fixed intervals, as used in the most previous work [17, 26, 27], does not yield good results. This algorithm uses rotation invariant template matching based on central projections and ring projections.

   c. The proposed algorithm uses a general technique not specific to each landmark.

v. The second cephalometric algorithm is optimized to further reduce the chance of misclassification, improve reliability and accuracy of landmark detection. In addition, it is more efficient in computations than the first algorithm.

vi. Performance analysis and comparison of recently proposed polar complex exponential transform is done with Zernike moments and angular radial transforms to find if further improvement is possible in cephalometric landmark detection using these descriptors. Polar complex exponential transform gives improved results for global matching of cephalograms but at a slower speed than angular radial transforms. Thus finally, a fast method for the computation of polar complex exponential transform is proposed. Polar complex exponential transform can be applied instead of applying angular radial transforms to further improve the performance of cephalometric image registration used to find the region of interest for each landmark.

1.7. Outline of the Thesis

The rest of the thesis is organized as follows:

Chapter 2 provides a comprehensive review of various techniques used for cephalometric enhancement, edge detection and landmark detection. In Chapter 3, cephalometric noise suppression has been investigated and a new algorithm is proposed for noise suppression. Chapter 4 discusses cephalometric contrast enhancement in detail and elaborates on a new technique proposed for contrast enhancement. Chapter 5 discusses two new techniques for pixel and subpixel level edge detection and their performance on cephalometric images. In Chapter 6 and Chapter 7, two new techniques for automatic landmark detection are proposed. Chapter 8 discusses the comparative performance of Zernike moments, angular radial transforms and polar complex exponential transforms for global matching of cephalogram images. A fast method to compute the polar complex exponential transform is also proposed in this Chapter. Finally, Chapter 9 summarizes and concludes the contributions and gives the future research directions.