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Cephalometric X-Ray Registration using Angular Radial Transform

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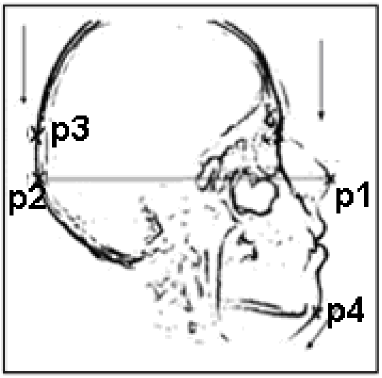
ABSTRACT
In this paper we propose a new cephalometric x-ray registration technique based on angular radial transform (ART). The registration is used as a first step in most hybrid cephalometric landmark detection algorithms to find the approximate landmark locations which are further used to find the exact landmark locations in the test x-ray image. All the existing cephalometric algorithms use features like distance between landmarks, distance between landmarks and their centre of gravity and their angular information for x-ray registration. The results achieved by the proposed technique are significantly better in terms of error and robustness.

Keywords
Cephalometric, Image Matching, Angular Radial Transform.

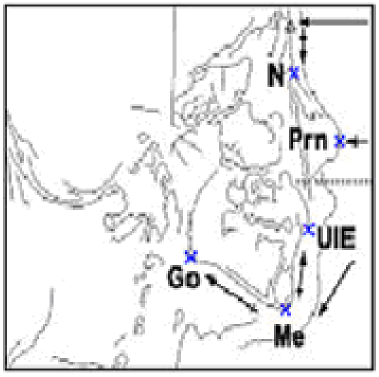
1. INTRODUCTION
Cephalometry is the scientific study based on a set of agreed upon feature points called landmarks on the skull to provide quantitative assessment of craniofacial morphology for diagnosing anomalies, monitoring therapy and growth predictions. Inconsistency and variability in landmark identification is a major source of error in this analysis. Motivation exists to automate this repetitive and time consuming process. Automatic cephalometric landmark detection has been subject of research for many years. There are around 15 traditional landmarks and some additional landmarks which are unique to a specific cephalometric analysis [1].

Newer techniques are mostly hybrid techniques which try to optimize the results by combining the techniques used in previous studies. In El Feghi et al[2] the process of landmark localization is carried out in two steps: deriving a smaller expectation window for each landmark using a trained neuro-fuzzy system (NFS) then applying a template-matching algorithm to pin point the exact location of the landmark. Four points are located on each image using edge detection. The four points are used to extract more features such as distances, shifts and rotation angles of the skull for training the neural network. Wei[3] Identify five reference landmarks using image processing using canny edge detector and handcrafted algorithms and another seven landmarks by pattern recognition based on the line and angular distance features extracted using the first five landmarks. Active shape model (ASM) is used to find all the feature points using shape partition of the image using the 12 reference landmarks. Rahele et al[4] find three reference points using susan edge detectors and knowledge based method and further use these to find features (line and angular) for training neural network. The results are further improved by using ASM [3] and template matching with the strategy used in [2]. The various reference landmarks used in different papers for feature extraction are shown in Fig 1.

A fundamental problem in medical image analysis is the integration of information from multiple images (intra-subject or inter-subjects), acquired using the same or different imaging modalities. This is achieved using image registration. Registration is the process of determining the correspondence between points in two images of the same scene.



(a)



(b)

Figure 1: a) Reference landmarks used for extracting features in a) [1] b) [2] and c) [3]

Image registration essentially consists of three steps:

- Feature detection: Salient and distinctive objects (contour or region based) in both training and test images are detected.
- Feature matching: The correspondence between the features in the training and test images image established using some distance measure.
- Image Transformation: Transforming the images to filter out location, scale and rotational effects. [2]

This paper proposes a new technique for cephalometric image registration which is more efficient in terms of accuracy and robustness in feature extraction in images of varying quality.

2. BACKGROUND AND PRIOR WORK

Most of the algorithms [3, 4, 5] use few reference landmarks on the x-rays to extract features based on distance and angles between the landmarks and between the landmarks and their centre of gravity. Features used in [4] are shown in Fig 2 . The landmarks used to compute the features are manually located in the training set images and located using handcrafted algorithms based on classical image processing techniques like edge detection. These features are used to find the training images whose distances to the input are less than a pre-defined threshold. The distance between two images is given by the Euler distance between their feature vectors.

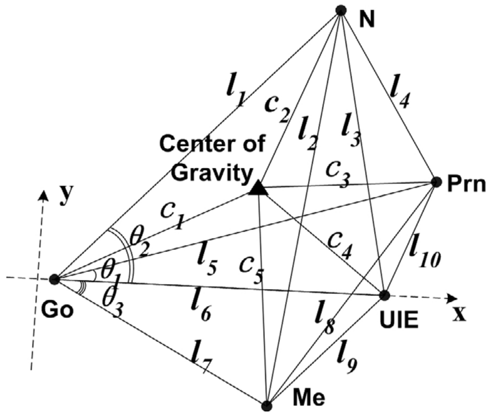


Figure 2: Features extracted from *UIE*, *Me*, *N*, *Go* and *Prn*

For each un-located reference landmark the selected training images are aligned to the input image by Procrustes algorithm [6] which iteratively computes the mean shape and aligns all the examples to it until convergence. The exact landmark locations are detected using the mean landmark with active shape model, local template matching, neural network etc.

Features extracted using landmarks are not robust. In the test image the landmarks required for feature extraction are obtained using handcrafted algorithm for each landmark based on classical image processing techniques. Techniques based on edge enhancement and edge detection for landmark detection depends on the quality of x-ray expressed in terms of sharpness (which is related to blur and contrast) and noise. Contrast and blur are dependent on tissues being examined. Noise is related to radiographic complexity of the region. Due to low contrast, many complex and overlapping structures and blurry nature of the x-rays the detected edges may suffer from false and missing edges and their location accuracy may be poor. This in term will affect the landmark detection accuracy and the features extracted from them.

In cephalometric images the contrast between the soft-tissue and bony structure is low, edges are blurred, and are very and. In such images it is difficult to detect contour based features. Region based shape descriptors such as moments are more reliable for shapes that have complex boundaries because they rely not only on the contour pixels but also on all pixels constituting the shapes. The proposed method explores the use of region based shape matching for cephalometric image registration.

3. MOMENT BASED FEATURE DESCRIPTORS

The Zernike moment is a type of orthogonal invariance moments proposed by Teague [7] in computer vision. An image can be better described by a small set of its Zernike moments than any other types of moments such as geometric moments, Legendre moments, in terms of mean square error. This shape descriptor has proved its superiority with respect to description capability and robustness to noise or deformations over other moment functions. A relatively small set of Zernike moments can characterize the global shape of a pattern effectively. Thus it is the most commonly used rotation-invariant pattern recognition technique used in image shape feature extraction and description [8, 9]. But their computational complexity is high.

The other important shape descriptors belonging to this class are pseudo-Zernike moments, orthogonal Fourier Moments (OFMMS) and angular radial transform (ART). The radial basis functions of ART [10, 11] are the sinusoidal functions unlike the three moments, whose radial basis functions are radial polynomials. The computational form of ART is similar to that of the moments. The transform has the same characteristics as the moments, minimum information redundancy, robustness to image noise and invariant to rotation. Two of the most important characteristics of ART which distinguishes it from the moments are that it is computationally very fast and the high order transforms do not suffer from numerical instability unlike ZMs, PZMs and OFMMs. Cephalometric landmark detection is real time application so fast computation is an important issue. Thus in this paper we explore the use of ART for cephalometric registration process. The ART features have the ability to describe the complex objects effectively and are invariant under rotation, scaling, translation and noise [12, 13, 14].

4. PROPOSED ALGORITHM

The algorithm is divided into three main steps

Step I Feature detection

This step works in two modes (offline and online). In offline mode the region based ART features of the training set images are computed and saved for future reference. In online mode the ART features of the query image are computed.

Computation of ART features

The ART coefficients of order n and repetition m for a continuous image function $f(x,y)$ in a unit disk are given by

$$A_{nm} = \iint_{x^2+y^2\le 1} V_{nm}^*(x,y)\, f(x,y)\,dxdy \tag{1}$$

Where the function $V_{nm}^*(x,y)$ is the complex conjugate of the ART basis function $V_{nm}^*(x,y)$ defined by

$$V_{nm}(x,y) = \frac{1}{2\pi} R_n(r) e^{jm\theta} \tag{2}$$

Where

$$R_n(r) = \begin{cases} 1, n = 0 \\ 2\cos(\pi n r), n > 0 \end{cases} \tag{3}$$

Where n is a non negative integer, m is an integer, $r = \sqrt{x^2 + y^2}$, $j = \sqrt{-1}$ and $\theta = \arctan(\frac{y}{x})$.

Step II: Matching of the ART Descriptors:

The correspondence between the ART features in the training and test images is established using a rigorously founded approach which takes both magnitude and phase information into consideration. The distance measure used is similar to the one proposed in [15] for Zernike moments. This distance measure provides a more accurate rotation-invariant similarity measure than considering only the Euclidean distance between magnitude part while keeping the computational complexity same.

Using the phase information with the magnitude improves the distance measure in terms of robustness against geometric deformation.

Distance between two images I and J is calculated as given in eq. 4 below, where A_{pq}^I and A_{pq}^J represents the ART coefficients with order p and repetition q of Image I and J .

Step III: Image Transformation

The five most similar training images to the query image are selected. These images are aligned to the input image by Procrustes algorithm [6] which iteratively computes the mean shape and aligns all the examples to it until convergence. The mean shape is used to extract all the un-located landmarks.

$$d_{I,J}^2(\phi) = \sum_{(p,q)\in D} \sum \frac{\pi}{p+1}\left[\left|A_{pq}^I\right|^2 + \left|A_{pq}^J\right|^2 - 2\left|A_{pq}^I A_{pq}^J\right| \cos\left(q\phi + [A_{pq}^J] - [A_{pq}^I]\right)\right] \tag{4}$$

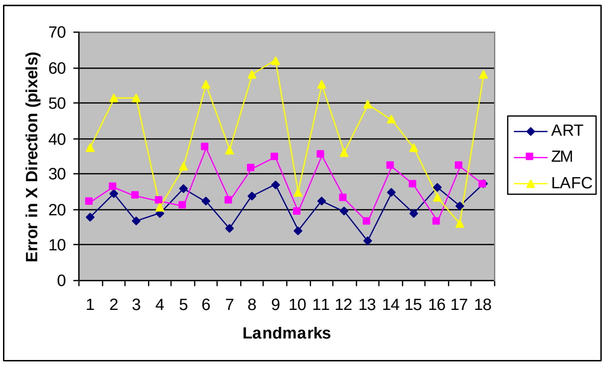
5. RESULTS AND DISCUSSIONS

Eighteen landmarks are selected for this experiment shown in Table 1. The selected landmarks are of different types and locations and should provide a reasonable test set for assessing the landmarks. Total 75 training image were collected randomly from the data set without any judgment of their quality, sex, and age. The system was tested using drop-one-out algorithm. Each time 74 images were used for training and one image was excluded for testing.

Table 1: List of Reference Landmarks and their Description

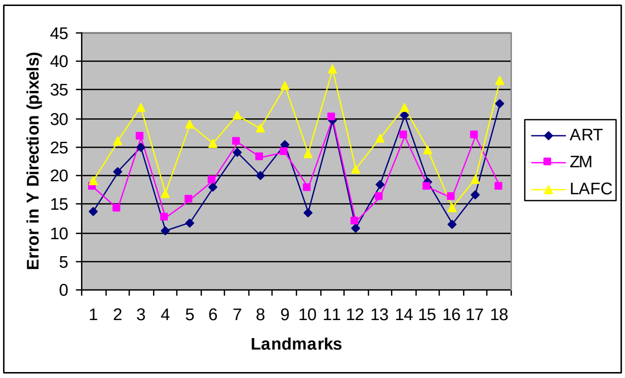
S.No	Name of	Landmark Description
1	Anterior	the tip of the bony anterior nasal spine, in the median
2	Pronasale	the most prominent point of the nose
3	Labrale	the median point in the lower margin of the lower
4	Condylion	most superior point on the head of the condyle
5	Supraorbitale	the most anterior point of the intersection of the
6	Labrale	the median point in the upper margin of the upper
7	Gonion	a constructed point, the intersection of the lines
8	Upper	the incisal edge of the maxillary central incisor
9	Point B	most anterior part of the mandibular base
10	Orbitale	the lowest point in the inferior margin of the orbit
11	Menton	the lowest point of the mandible
12	Nasion	the most anterior point of the frontonasal suture in
13	Posterior	the intersection of a continuation of the anterior wall
14	retrognation	More posterior inferior point of the jaw symphysis
15	Point A	the deepest midline point in the curved bony outline
16	Porion	the superior point of the external auditory meatus
17	Sella	The midpoint of the hypophysial fossa
18	Pognion	most anterior point of the bony chin, in the median

The performance of the ART descriptor based image registration was evaluated by comparing its performance with ZM descriptor and landmark based line and angular features. The three algorithms were implemented in C. The average error in pixels in x direction and y direction is shown in Fig 3 and Fig 4 respectively. Based on the comparative experimental results, the ART descriptor performs better than the other two techniques. The performance of ART descriptor in X directions is the best and in Y direction it is comparable or slightly better than ZM descriptor for most landmarks. Line and angular features give the poorest results due to difficulty in obtaining good edge results which further effect the derived landmark positions used for calculating these features. It was expected that ZM descriptor will give better or similar results to the ART descriptor and the only difference will be the speed benefit of ART. But in this case the ART descriptor out performed the ZM descriptor as evident from the results in Fig 3 and Fig 4. The reason for the inferior results of the ZM descriptor maybe its variance under translation and scaling as reported by [16]. Thus additional preprocessing will be needed for the ZM descriptor to cope with the translated and scaled images. The results of ART descriptor are nearly similar to the results of line and angular features (Fig 5 and Fig 6) when we consider the ideal case and use the exact manually marked landmarks for the query image instead of using the landmarks detected using hand annotated edge based method. This shows the robustness of ART descriptor even if the quality of cephalometric images is poor and edge based methods fail and give poor results.



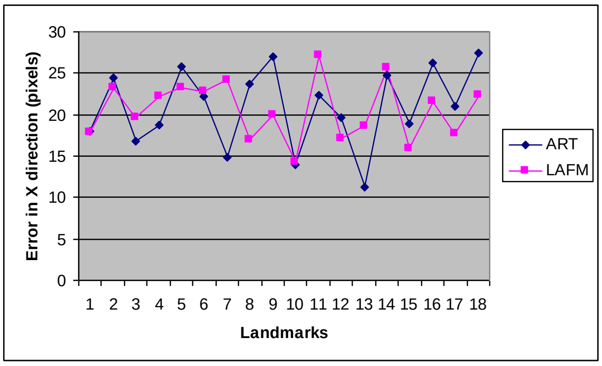
* LAFC: Length and angular features using computed reference landmarks

Figure 3: Average error (pixels) in X direction for the three methods for 18 landmarks given in Table 1.



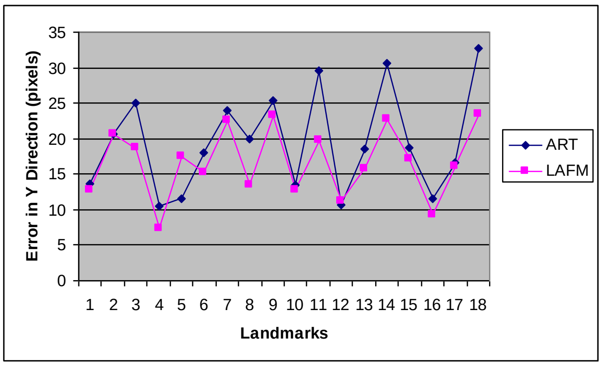
* LAFC: Length and angular features using computed reference landmarks

Figure 4: Average error (pixels) in Y direction for the three methods for 18 landmarks given in Table 1.



* LAFM: Length and angular features using manually marked reference landmarks

Figure 5: Average error (pixels) in X direction for the three methods for 18 landmarks given in Table 1.



* LAFM: Length and angular features using manually marked reference landmarks

Figure 6: Average error (pixels) in Y direction for the three methods for 18 landmarks given in Table 1.

6. CONCLUSIONS

Initial results of the proposed method are good. The algorithm will be tested on a large dataset. Further test will be conducted to compare its performance with improved scale invariant Zernike moments and also by combining ART based region shape descriptor with efficient contour based shape descriptors.

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