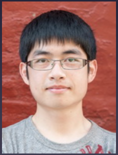
Cephalometric Landmark Tracing Using Deformable Templates

Yuxin Chen[†], Brian Potetz[†], Bo Luo[†], Xue-wen Chen[†], Yunfeng Lin[‡]

[†] *Department of EECS, The University of Kansas, Lawrence, KS, USA*

[‡] *State Key Laboratory of Oral Diseases, Sichuan University, Chengdu, China*

Background

1. Cephalometric analysis is the study of the dental and skeletal relationships in human head.
2. A cephalogram provides information about the sagittal and vertical relations of hard contour and soft tissue landmarks profile.

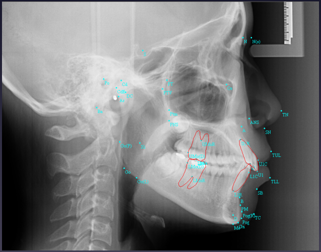


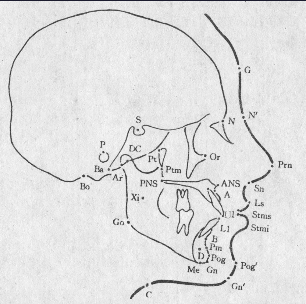
Table I
LANDMARKS FOR CEPHALOMETRIC TRACING

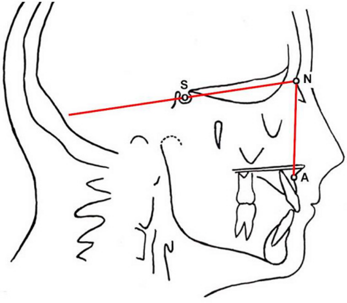
Cranial	Supramaxilla	Mandible	Soft tissue
N. Nasion **S.** Sella **Ba.** Basion **Bolton**	**O.** Orbitale **ANS.** Anterior Nasal Spine **PNS.** Posterior Nasal Spine **Ptm.** Pterygoma-xillary Fissure **A.** Subspinale **SPr.** Superior Prosthion **UI.** Upper Incisor	**Co.** Condylion **Ar.** Articulare **Go.** Gonion **B.** Supramentale **Id.** Infradentale **Li.** Lower Incisor **Po.** Pogonion **Me.** Menton **Gn.** Gnathion	**G.** Glabella **Ns.** Nasion of Soft Tissue **E.** Eye **Prn** **Sn.** Subnasale **UL** **LL** **Pos.** Pogonion of Soft Tissue

Background

Example

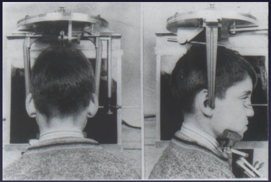
A patient with a skull configuration of low-positioned Sella might have a small *SNA* reading (retruded maxilla)

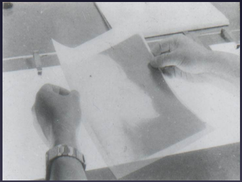


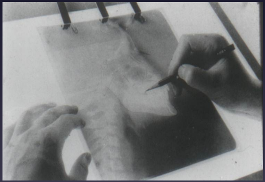


Motivation

- Identifying the cephalometric landmarks, lines, and faces is a difficult task for human eyes.
    - X-ray images are not always clearly projected.
    - Landmark detection in cephalometry has a high requirement in both quality and quantity.







Motivation

1. Currently available cephalometric assessment systems are not satisfiable due to the large variability in skull structures.
   - most of the existing approaches are suffering from low efficiency or sensitive to noices
   - some of them depend highly on user initialization.

Motivation

Tracking anatomic structures using deformable models

1. Deformable templates can be used to detect changeable objects in reasonable time without initialization.
   - i.e., deformable hand template [Coughlan 2000]
2. It allows researcher to bring heuristic knowledge to bear on the model-based image interpretation task.

Our idea

To design a robust deformable model that employs important (pairwise) relations between landmarks.

A simplified case

Deformable chain - Hand template [Coughlan 2000]

Notations

Let a chain of landmarks $\{X_i\}$ represent a 2D contour, with an associated chain $\{\theta_i\}$ representing the normal orientation at each point ($i = \{1, 2, \ldots, N\}$). Each point X_i has two components (x_i, y_i); (X_i, θ_i) is denoted as $\mathbf{q}_i$ for discussion simplicity.

A simplified case

Deformable chain - Hand template [Coughlan 2000]

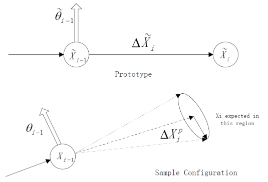


Figure 3. The prototype displacement $\Delta\tilde{X}_i$ need only be rotated by $\theta_{i-1} - \tilde{\theta}_{i-1}$ to make a displacement prediction $\Delta X_i^p \cdot X_i$ is expected in a neighborhood of $X_i^p = X_{i-1} + \Delta X_i^p$.

1. Orientation model:

$$P(\theta_i|\theta_{i-1}) = G(\theta_i - \theta_{i-1} - (\tilde{\theta}_i - \tilde{\theta}_{i-1}); \sigma_{a,i})$$

2. Position model:

$$\begin{aligned} P(X_i|X_{i-1}, \theta_{i-1}) = \; & G([\Delta X_i - \Delta X_i^p] \cdot \Delta\hat{X}_i^p; \sigma_{t_i}) \cdot \ldots \\ & G([\Delta X_i - \Delta X_i^p]^{\perp} \cdot \Delta\hat{X}_i^p; \sigma_{n_i}) \end{aligned}$$

A simplified case

Deformable chain - Hand template [Coughlan98]

Each of the chain-shaped landmark (i.e., at stage *i*) only depends on its adjacent landmark.

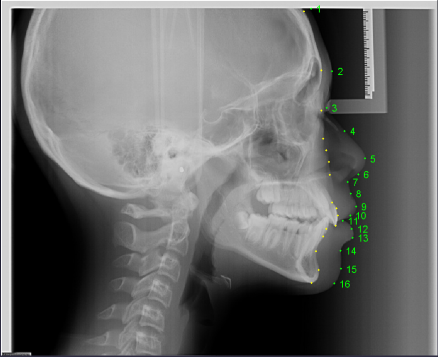
$$P(\mathbf{q}_i|\mathbf{q}_{i-1}) = P(\theta_i|\theta_{i-1})P(X_i|X_{i-1}, \theta_{i-1})$$

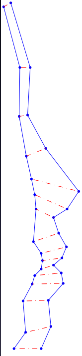
The prior of the entire configuration could be represent as:

$$P(\mathbf{q}_1, \mathbf{q}_2, \ldots, \mathbf{q}_N) = \prod_{i=2}^{N} P(\mathbf{q}_i|\mathbf{q}_{i-1})$$

The cephalometric model

The geometric prior



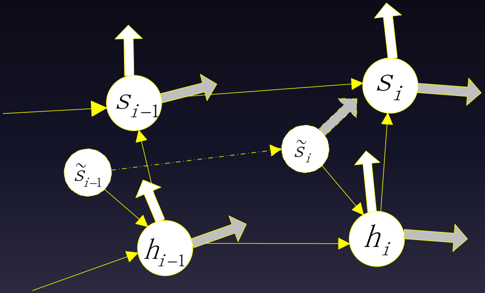


The relation between the soft tissue landmarks and the hard contour landmarks are more consistent!

The cephalometric model

The geometric prior

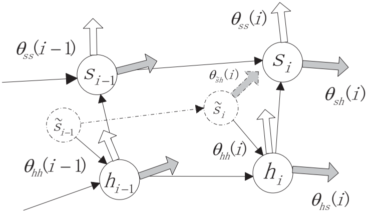
$$\begin{cases} h_i \leftarrow (h_{i-1}, \tilde{s}_i) \\ s_i \leftarrow (s_{i-1}, h_i) \\ h_i \perp s_{i-1} | h_{i-1} \\ \tilde{s}_i \perp h_{i-1} | \tilde{s}_{i-1} \end{cases}$$



In the cephalometric model, each landmark at state i has two dependencies.

The cephalometric model

The geometric prior



We can revise the deviation measurement expressed in the hand template to accommodate our model:

$$
\begin{cases}
P(h_i|h_{i-1}) = P(\theta_{hh_i}|\theta_{hh_{i-1}})P(X_{h_i}|X_{h_{i-1}}, \theta_{hh_{i-1}}) \\
P(h_i|\tilde{s}_i) = P(\theta_{hs_i}|\theta_{\tilde{s}h_i})P(X_{h_i}|X_{\tilde{s}_i}, \theta_{\tilde{s}h_i}) \\
P(s_i|s_{i-1}) = P(\theta_{ss_i}|\theta_{ss_{i-1}})P(X_{s_i}|X_{s_{i-1}}, \theta_{ss_{i-1}}) \\
P(s_i|h_i) = P(\theta_{hs_i}|\theta_{hs_i})P(X_{s_i}|X_{h_i}, \theta_{hs_i})
\end{cases}
$$

1. An imaging model describes the geometric and photometric mappings between image data and a specific configuration.
2. Our imaging model jointly employs two sets of data derived from multiple edge/corner detectors
   - We integrate morphological edge detection method with a set of Canny edge detectors to localize a wide range of edges in the X-ray image.
   - We include the phase congruency (PC) map $I_p(X)$ in our imaging model, recording features at all kind of phase angle.

The cephalometric model

The imaging model

Given the configuration of a set of candidate landmarks $\mathbf{q} = \{\mathbf{s}_1, \mathbf{h}_1, ..., \mathbf{s}_N, \mathbf{h}_N\}$, the data likelihood function is

$$P(\mathbf{D}|\mathbf{q}) = \prod_I P(\mathbf{D}(X)|\mathbf{q})$$

We assume that the imaging model factors into separate probabilities on the edge map and PC map over all pixels in the lattice,

$$P(\mathbf{D}(X|\mathbf{q})) = P(I_e(X|\mathbf{q}))P(I_p(X|\mathbf{q}))$$

and we model the $I_e(X|\mathbf{q})$ and $I_p(X|\mathbf{q})$ with Gaussian distributions,

$$P(I_e(X|\mathbf{q}_i)) = G(I_e(X) - \mu_{e_i}, \sigma_{e_i})$$
$$P(I_p(X|\mathbf{q}_i)) = G(I_p(X) - \mu_{p_i}, \sigma_{p_i})$$

1. It is well known that inference in discrete graphical models with low tree-width can be done using dynamic programming and belief propagation.
2. We the apply a dynamic programming optimization algorithm to find the MAP

$$MAP = argmax_{\mathbf{s},\mathbf{h}} P(\mathbf{s}_1, \mathbf{h}_1, \ldots, \mathbf{h}_N) P(\mathbf{D} | \mathbf{s}_1, \mathbf{h}_1, \ldots, \mathbf{h}_N)$$

If we denote the score of best path to stage i as $\mathcal{E}_i$, then the DP algorithm could be formulized as follows.

$$\begin{cases} \mathcal{E}_i(\mathbf{s},\mathbf{h}) = \max\limits_{\mathbf{s}_{i-1},\mathbf{h}_{i-1}} \{\mathcal{E}_{i-1}(\mathbf{s}_{i-1},\mathbf{h}_{i-1}) + \mathcal{C}_i(\mathbf{s},\mathbf{h})\} \\ argmax_{\mathbf{s},\mathbf{h}} \mathcal{E}_0(\mathbf{s},\mathbf{h}) = (\mathbf{s}_0,\mathbf{h}_0) \end{cases}$$

To trace back the optimal path, we store the previous landmark for each candidate landmark at each stage in a path matrix, i.e.,

$$Path(\mathbf{s},\mathbf{h}) = argmax_{\mathbf{s}_{i-1},\mathbf{h}_{i-1}} \{\mathcal{E}_{i-1}(\mathbf{s}_{i-1},\mathbf{h}_{i-1}) + \mathcal{C}_i(\mathbf{s},\mathbf{h})\}$$

Data set

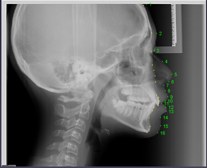
1. We have implemented the proposed algorithm on a cephalometric database from a population of 754 Chinese patients.
    - 84 manually marked cephalograms with multivariate cranial and facial structures are selected as training images
    - Another 30 are selected for testing purpose
2. We model the deformable template using 16 landmark pairs along the facial contour, among which 10 hard landmarks and all 12 soft tissue landmarks and are covered.

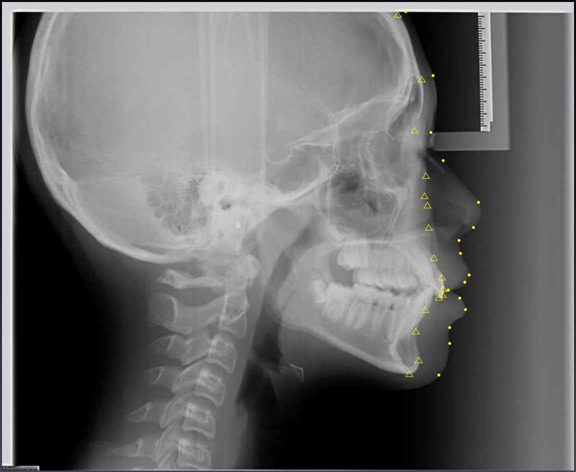
Settings

1. We run our dynamic programming optimization algorithm over the downsampled version of a testing image with a reproduced image resolution of 800*650 pixels.
2. For each stage, we scan alternately (every 5 pixels) within a window size of 40*40.
    - The average time for one iteration is 245 seconds.

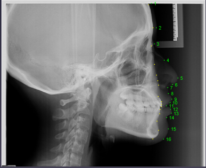
Results

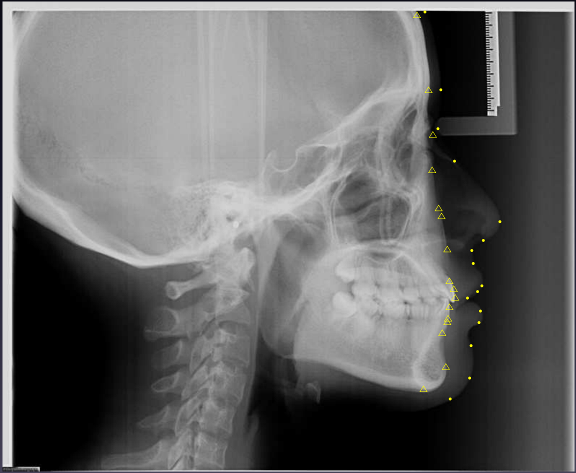
Illustrative example 1





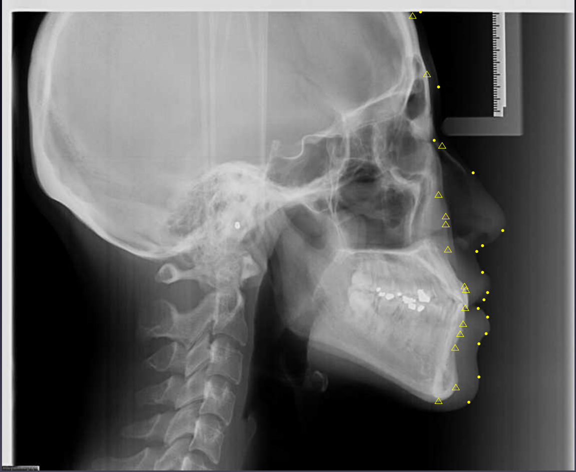
Results
Illustrative example 2





Results

Illustrative example 3



Evaluation

Measurement: reliability & offset

Definition

The cephalometric assessment reliability $R(x_i, y_i)$ is defined as the cosine similarity between the real edges between landmarks and detected edges (between detected landmarks and the real landmarks at the previous states):

$$R(x_i, y_i) = \frac{(x_i - \tilde{x}_{i-1}, y_i - \tilde{y}_{i-1}) \cdot (\tilde{x}_i - \tilde{x}_{i-1}, \tilde{y}_i - \tilde{y}_{i-1})}{\|(x_i - \tilde{x}_{i-1}, y_i - \tilde{y}_{i-1})\| \|(\tilde{x}_i - \tilde{x}_{i-1}, \tilde{y}_i - \tilde{y}_{i-1})\|}$$

Definition

Offset is the average distance between detected landmark and real (manually marked) landmark.

Evaluation

Performance vs. different landmarks

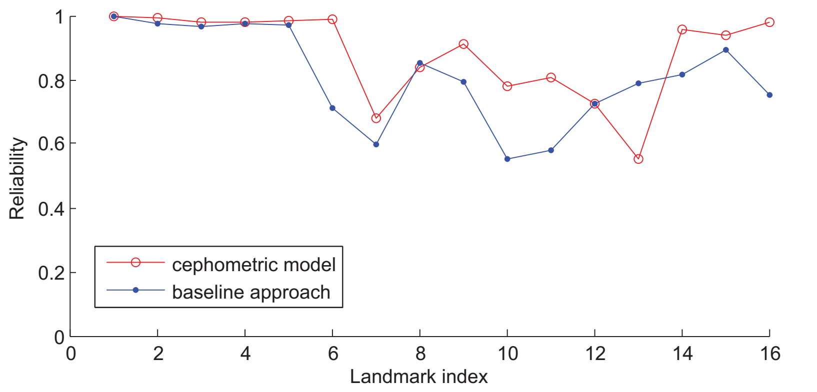


Figure: reliability across all the soft tissue landmarks

Evaluation

Performance vs. different landmarks

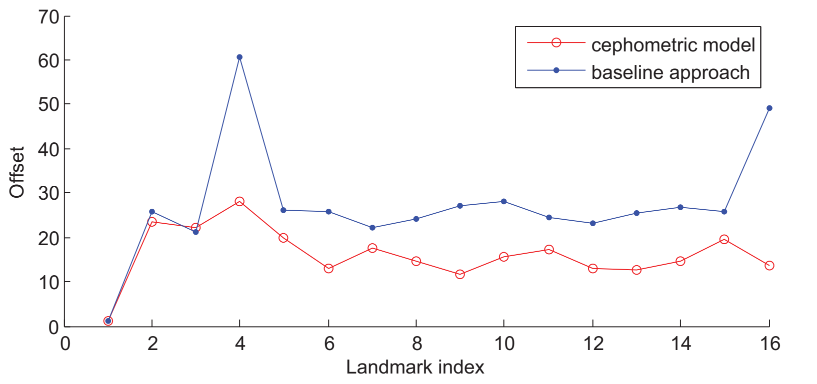


Figure: offset across all the soft tissue landmarks

Evaluation

Performance vs. iterations

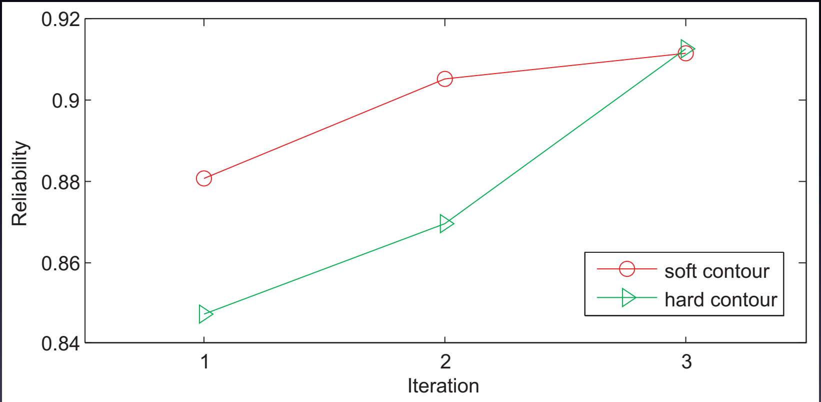


Figure: (a) reliability with different iterations

Evaluation
Performance vs. iterations

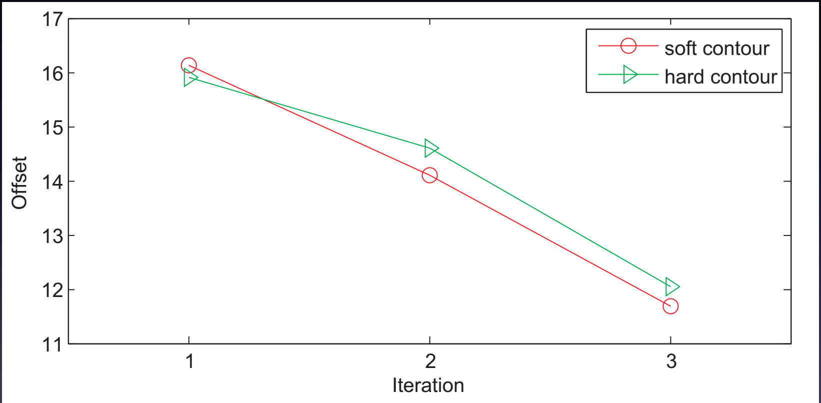


Figure: detection offset with different iterations.

Thank you!

Questions?