KU Leuven

Computer Vision

Erasmus Program

Incisor Segmentation

Authors:

Alejandro Rodriguez Salamanca: r0650814
Fernando Collado Egea: ???

June 6, 2017

Contents

1 Introduction **2**

2 Active Shape Model **2**

2.1 Load data . . . 2

2.2 Align the training set . . . 2

2.3 Principal Component Analysis . . . 3

3 Grey Level Models **3**

4 Preprocess images **4**

5 Initialization **5**

5.1 Manual . . . 5

5.2 Automatic . . . 5

6 Fit the model **5**

7 Results **5**

8 Improvements **5**

8.1 Multi-resolution Active Shape Model . . . 5

8.2 Width of Search Profile . . . 5

8.3 Landmarks Grouping . . . 5

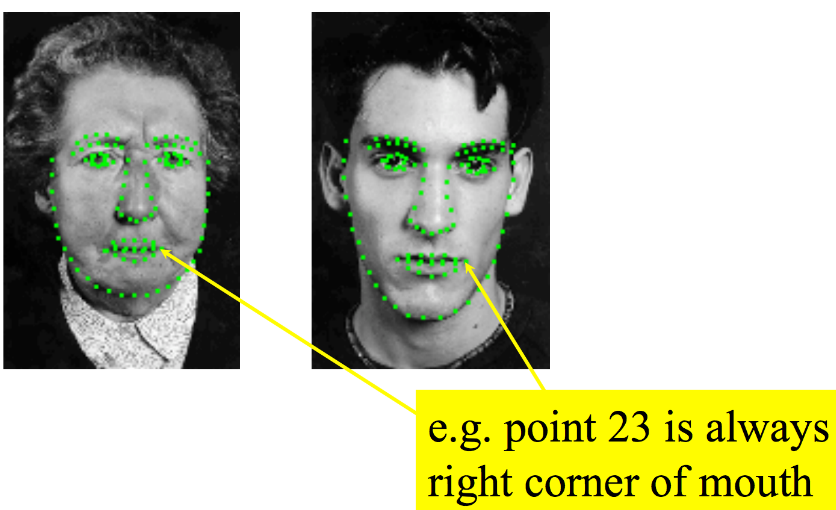
1 Introduction

2 Active Shape Model

Active shape models are statistical models of the shape of objects which iteratively deform to fit to an example of the object in a new image.

2.1 Load data

For this assignment we are provided by a set of landmarks, each one containing a list of points corresponding with the shape of a tooth. Those landmarks should be used to build an Active shape model. The first step is to load the landmarks. They are stored in list form, following the format $[X_1, Y_1, \ldots, X_n, Y_n]^T$. To increase the number of samples, the mirrored version of the landmarks is also loaded.



2.2 Align the training set

Once the landmarks are loaded, the training set must be aligned in order to compare equivalent points from different shapes. This alignment is done by scaling, rotating and translating the training shapes using the following algorithm:

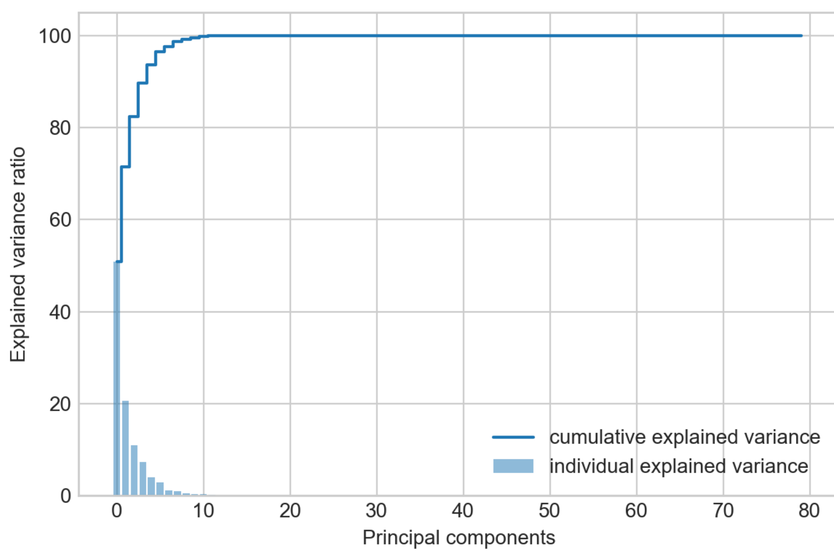
Rotate, scale and translate each shape to align with the first shape in the set;
while *process has not converged* **do**
  Calculate the mean shape from the aligned shapes;
  Normalize the orientation, scale and origin of the current mean to suitable defaults;
  Realign every shape with the current mean;
end

Algorithm 1: Procrustes Analysis

2.3 Principal Component Analysis

The set of aligned shapes contains as much dimensions as landmarks have each shape. To reduce the dimensionality of the dataset and get rid of the extra dimensions, Principal Component Analysis is applied. It uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The first principal component has the largest possible variance and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components.

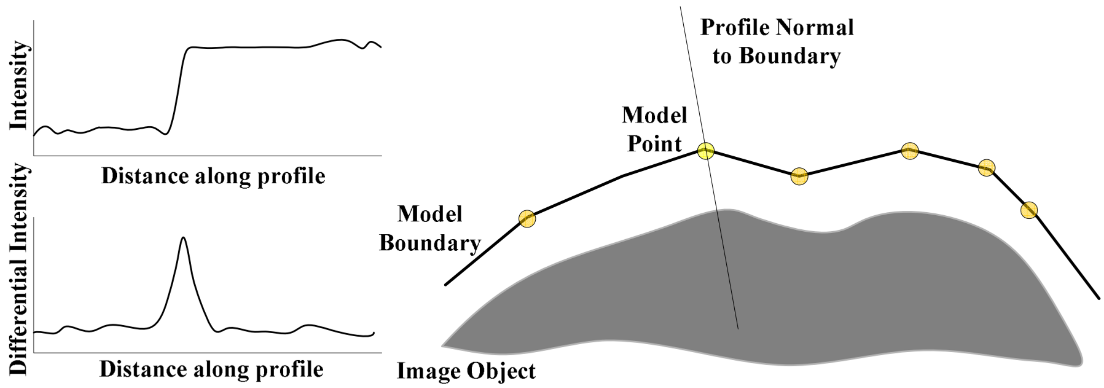
The first 8 components hold more than 98% of variance. The dimension of the dataset is reduced from 80 to 8.



3 Grey Level Models

We can model the appearence of an object by examining the statistics of grey levels in regions around each of the labelled model points in the training images. As with the shape, the grey-level environment can be modelled by a mean and a number of modes of allowed variation.

For every landmark point j in the image i of the training set, we extract a gray level profile g_{ij} , of length np pixels, centered around the landmark point. To reduce the effect of global intensity changes, we do not use the actual vector g but use the normalized derivative instead.



4 Preprocess images

Radiographs are images inherently noisy. In order to locate the teeth precisely, the original radiographs should be converted to images as noiseless as posible, but sharp enough to locate the edges of the teeth. For this purpose the following algorithms and transfomations are used:

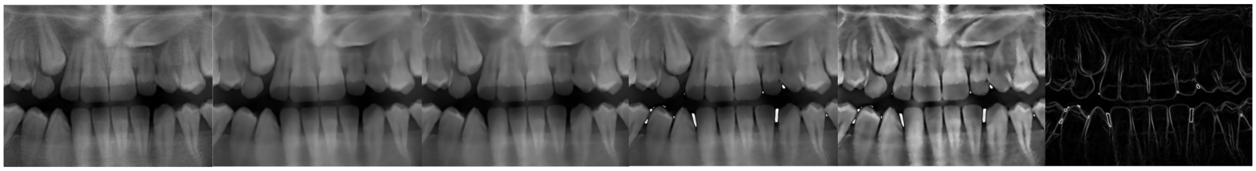
1. **Non-Local Means Denoising** - This algorithm performs denoising replacing the color of a pixel with an average of the colors of similar pixels. With the correct parameters, the result with have less noise than the original image, maintainig the image sharp.

2. **Top hat** - Is the difference between an input image and its opening. It extracts small elements and details from given images. The result of this transform is substracted to the original image to remove objects that are brighter than the surroundings.

3. **Black hat** - Is the difference between an input image and its closing. It performs the opposite effect than top hat. The result of this transformation is substracted to the original image to remove objects that are darker than the surroundings.

4. **CLAHE** - This name stands for Contrast Limited Adaptive Histogram Equalization. In this, image is divided into small blocks called "tiles". Then each of these blocks are histogram equalized as usual. If any histogram bin is above the specified contrast limit those pixels are clipped and distributed uniformly to other bins before applying histogram equalization.

5. **Edge detection with Sobel and Laplacian** - Sobel edge detector is a gradient based method based on the first order derivatives. It calculates the first derivatives of the image separately for the X and Y axes. The Laplacian of an image highlights regions of rapid intensity change.



5 Initialization

5.1 Manual

5.2 Automatic

6 Fit the model

7 Results

8 Future Improvements

8.1 Multi-resolution Active Shape Model

To improve the efficiency and robustness of the detection, a multi-resolution model can be used.

At the base of the pyramid it is the original image and the level is the lowest (level 0). The image in the higher level is formed by subsampling the former image then we obtain a lower resolution version of the image with half number of the pixels along each dimension. Subsequent levels are obtained by further subsampling.

With this method, the initial fit of the model to approximate will vary faster in position and orientation, and this fit will be improved and refinated in each level of the pyramid.

8.2 Width of Search Profile

In the implemented algorithm, search profile is only along a single line when searching forthe suggested movements of landmarks. But this search technique could be affected by noise in the image. To avoid this problem, the search space could be expanded adding some width to it.

8.3 Landmarks Grouping

As we have seen new allowed shapes should comply with the constraint that the range of b must be in the inverval $-3\sqrt{\lambda} \leq b \leq 3\sqrt{\lambda}$, where λ is the eigenvalue result of the principal component analysis. But some of the shape variation isnt decided by a single principal component, and unexpected shapes could still apear even with the range of b limited. This problem can be avoided grouping ladmarks that tend to move together.