CHAPTER 2   TOOTH REGION EXTRACTION

In this chapter, we describe how to extract teeth from a dental image. First problem we encounter is what color space suits for extracting teeth from a dental image. After analyzing three kinds of color space in section 2.1, we select HSI color space. Then we need know how to classify soft tissue and teeth regions in section 2.2. Finally, we extract teeth from a dental image by using removing non-tooth regions.

2.1 Selection of Color Spaces

Extracting tooth regions requires choosing an appropriate color space which can distinguish tooth color from other classes in this space. Many color space have been experimented and presented in research publication. Examples of commonly used color spaces are RGB, YCbCr and HSI. And the discriminative ability for tooth and soft tissue colors is our major concern. In this section, we compare the discriminative ability of teeth color and soft tissue color in RGB, YCbCr, and HSI color space.

2.1.1 RGB color space

The advantage of the RGB color space is that original color images are usually represented in the RGB format. Accordingly, no additional computation of any transformation is required. Nevertheless, color information and intensity are coupled together in this color space. From Fig. 2.1.1 to Fig. 2.1.3 show the distribution of tooth region and soft tissue in R, G, and B in sequence.
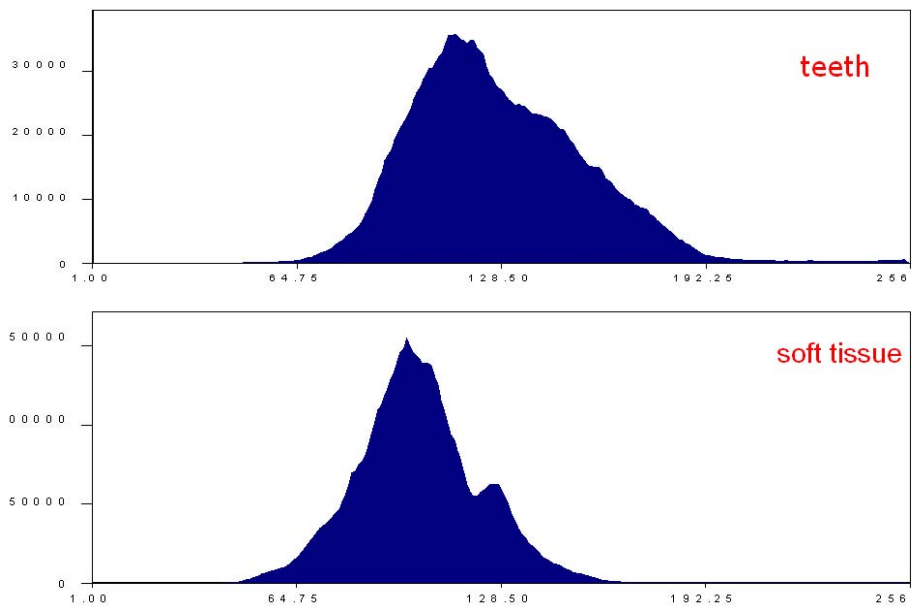
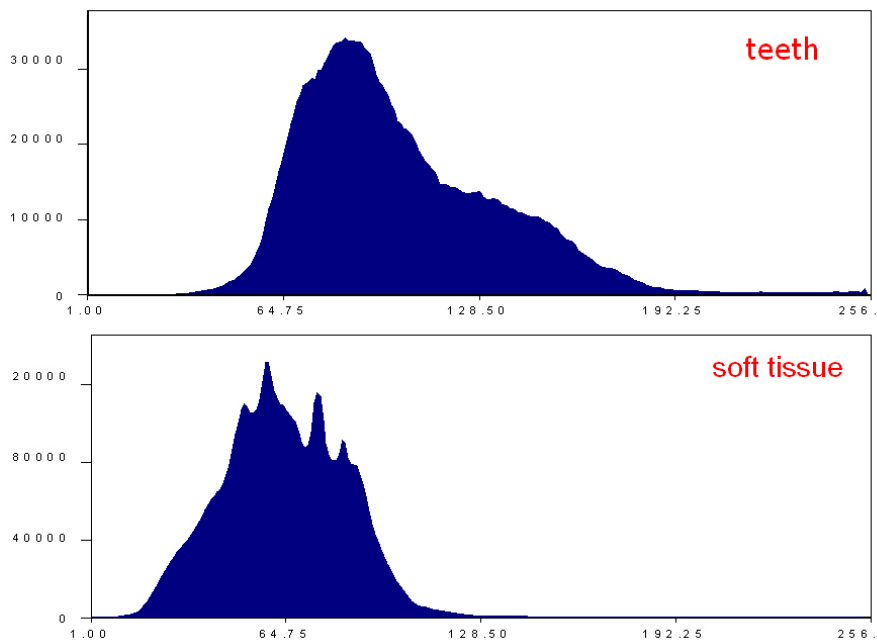Fig. 2.1.1　Distribution of tooth regions and soft tissue regions in R

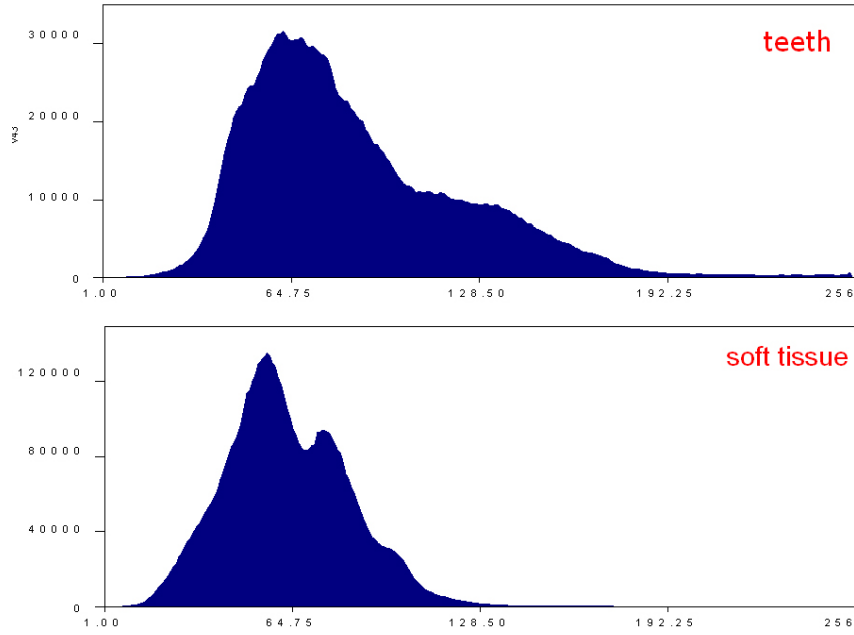Fig. 2.1.2　Distribution of tooth regions and soft tissue regions in G

Fig. 2.1.3   Distribution of tooth regions and soft tissue regions in G

2.1.2 YCbCr color space

Another common color space is YCbCr. We analyze the ability of distinguishing between teeth color and soft tissue color. The transformation from RGB into YCbCr color space is listed as follows.

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.257 & 0.504 & 0.098 \\ -0.148 & -0.291 & 0.439 \\ 0.439 & -0.368 & -0.071 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} \ \ldots\ldots\ldots \ (\text{Formula 2.1.1})$$

The distribution of tooth regions and soft tissue regions in YCbCr are shown from Fig. 2.1.4 to Fig. 2.1.6 in sequence.
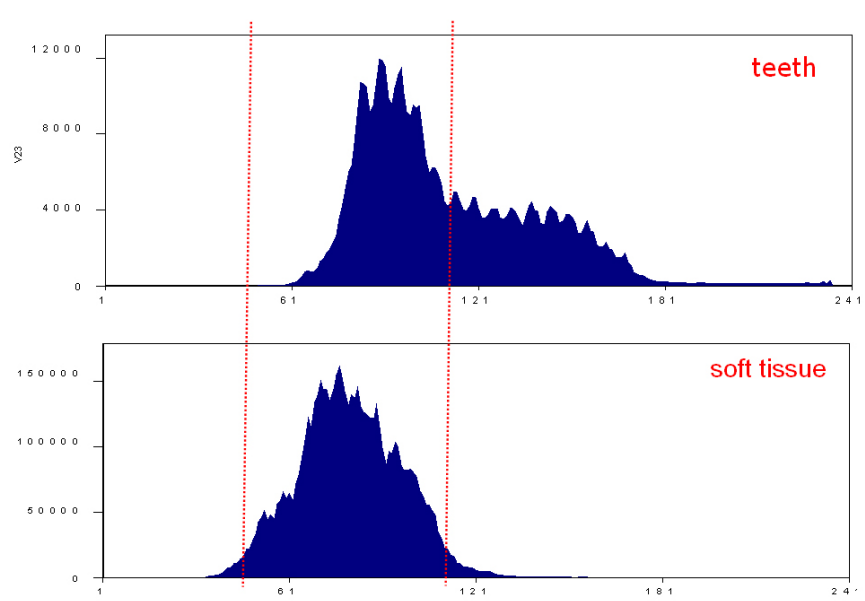
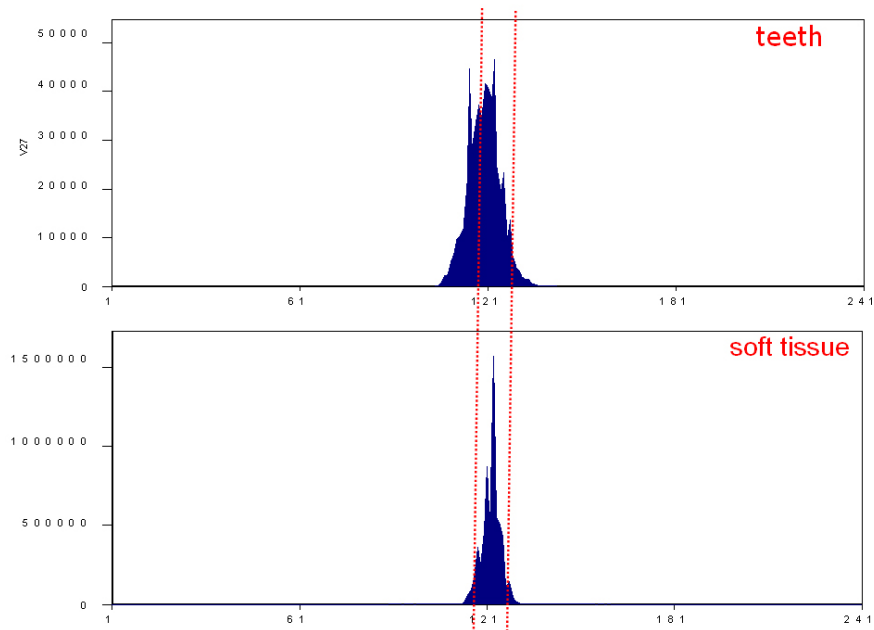Fig. 2.1.4   Distribution of tooth regions and soft tissue regions in Y

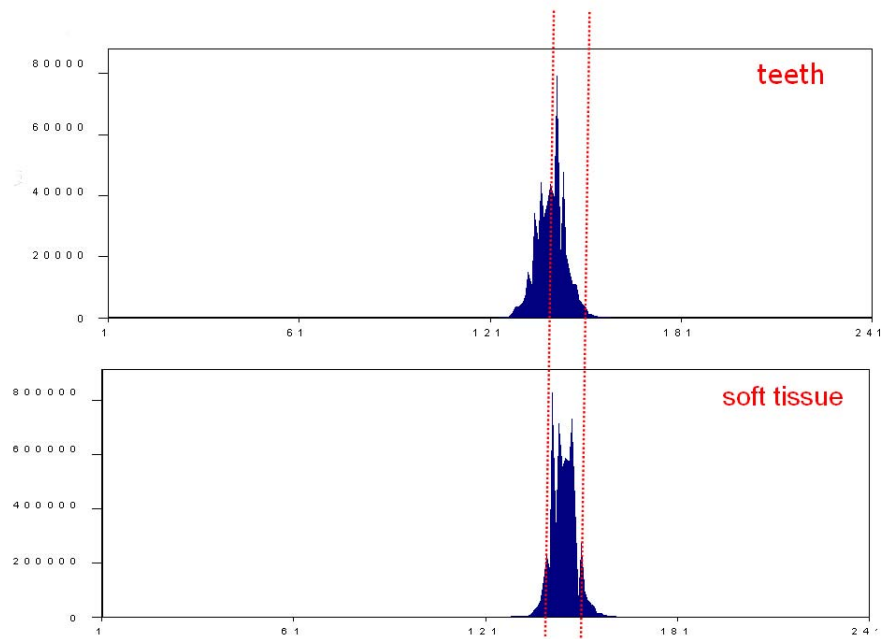Fig. 2.1.5   Distribution of tooth regions and soft tissue regions in Cb

Fig. 2.1.6　Distribution of tooth regions and soft tissue regions in Cr

All data vectors of tooth and soft tissue regions concentrate together such that we cannot separate tooth and soft tissue effectively in YCbCr color space. So using YCbCr is no obvious discriminative ability for extracting tooth regions.

2.1.3 HSI color space

HSI color space is used for representing the human color perception. The hue is a color attribute that describes a pure color and saturation is a measure of the degree to which a pure color is diluted by the white light. The advantage of HSI color space is to allow independent control over hue, saturation, and intensity. The transformation from RGB into HSI is described as follows:

$$H = \begin{cases} \theta, & if\ B \leq G \\ 360 - \theta, & if\ B > G \end{cases}, \quad where\ \theta = \cos^{-1}\left(\frac{\frac{(R-G)+(R-B)}{2}}{\sqrt{(R-G)^2 + (R-B)(G-B)}}\right)$$

$$S = 1 - \frac{3 \times min(R, G, B)}{R + G + B}$$

$$I = \frac{R + G + B}{3}$$

Formula 2.1.2

The distribution of tooth regions and soft tissue regions in hue is shown in Fig. 2.1.7.
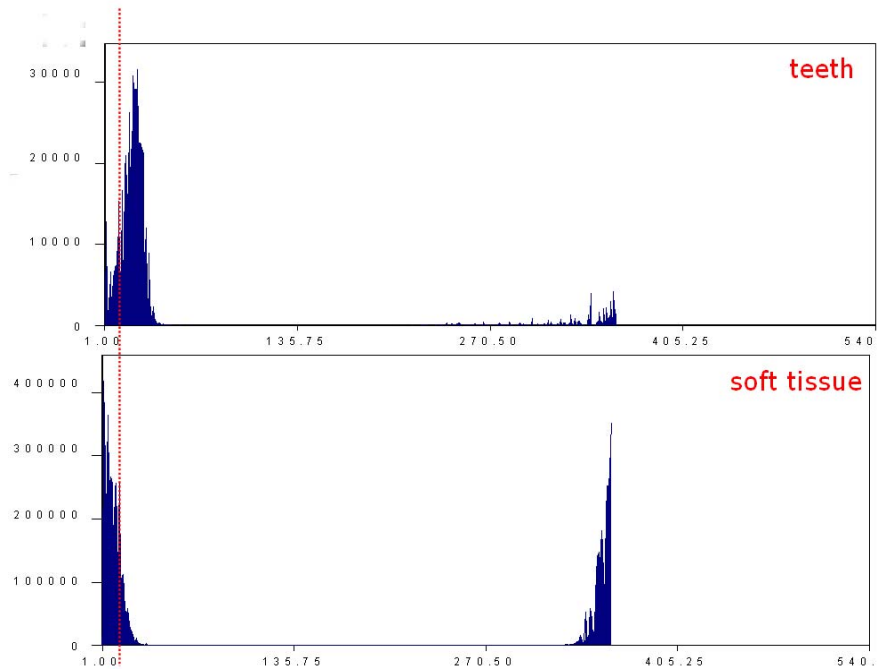

Fig. 2.1.7   Distribution of tooth regions and soft tissue regions in hue

The distribution of soft tissue regions locates on two side of Fig. 2.1.7 in hue. For convenient analysis, we shift hue value if hue value less than 180. The distribution of tooth regions and soft tissue regions become as follows:

15

$$\begin{cases} if\ Hue < 180 \implies \text{shift } (\textit{ie. hue } = \textit{ hue } + \textit{ 360}) \\ if\ Hue >= 180 \implies \text{not shift} \end{cases}$$
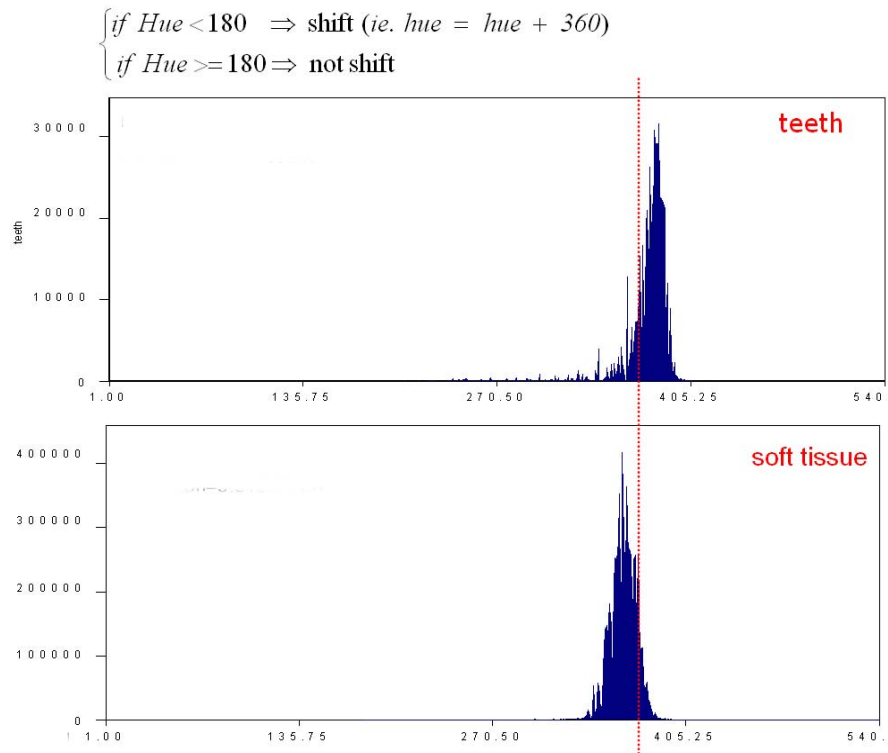

Fig. 2.1.8   Distribution of tooth regions and soft tissue regions in hue after shifting

The distribution of tooth regions and soft tissue regions in saturation and intensity are shown in Fig. 2.1.9 and Fig. 2.1.10 respectively.
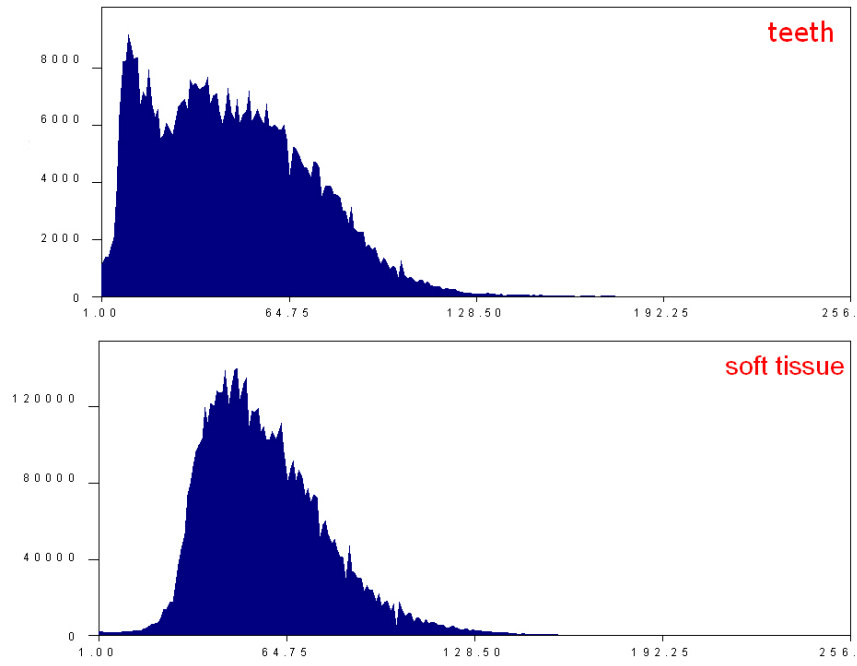
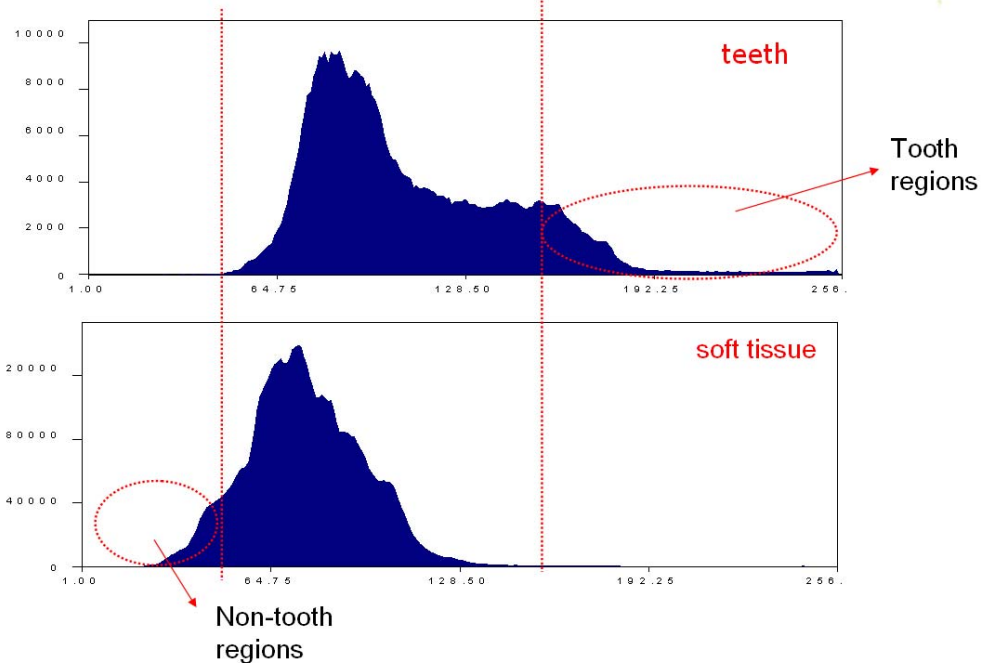Fig. 2.1.9   Distribution of tooth regions and soft tissue regions in S

Fig. 2.1.10   Distribution of tooth regions and soft tissue regions in I

For intensity equal or larger than 160 or less than 49, teeth and soft tissue in intensity have less overlapping area. Therefore, we can use intensity to help distinguish between tooth and soft tissue regions.

$$\text{if } I(i,j) \geq 160, \text{ then assign } (i,j) \text{ to teeth}$$
$$\text{if } I(i,j) < 49, \text{ then assign } (i,j) \text{ to non - teeth}$$

In hue, teeth and soft tissue have less overlapping area. And variance of hue is smaller than others. Hue has better discriminative ability than others in extracting tooth regions. After the above analysis, we infer that HSI color space is more suitable for discriminative ability of tooth regions and soft tissue regions.

2.2 Classification of Soft Tissue and Teeth

2.2.1 Teeth and soft tissue statistics

We collect teeth and soft tissue statistics using two steps.

Step 1: Extract teeth and soft tissue regions from different color dental images manually. Samples of teeth and soft tissue collected are depicted in Fig. 2.2.1 and Fig. 2.2.2.

Step 2: Transform the teeth and soft tissue samples into the HSI color space and collect all transformed hue and intensity value to form histograms.
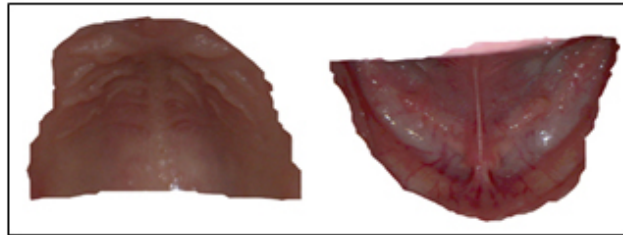
Fig. 2.2. 1   Samples of teeth

Fig. 2.2.2   Samples of soft tissue

2.2.2 Threshold selection

(A) A fixed threshold

Distributions of the hue feature on teeth and soft tissue are approximately normal. Hence, we can use a Bayesian decision rule to distinguish soft tissue and teeth regions. The Bayesian Decision Rule is:

$$P(teeth \mid X) = \frac{P(teeth)P(X \mid teeth)}{P(X)}$$

$$P(non\text{-}teeth \mid X) = \frac{P(non\text{-}teeth)P(X \mid non\text{-}teeth)}{P(X)}$$

$$\begin{cases} Cost_{teeth} \times P(teeth \mid X) > Cost_{non\text{-}teeth} \times P(non\text{-}teeth \mid X) \Rightarrow status = teeth \\ Cost_{teeth} \times P(teeth \mid X) < Cost_{non\text{-}teeth} \times P(non\text{-}teeth \mid X) \Rightarrow status = non\text{-}teeth \end{cases}$$

The decision boundary determined by the Bayesian rule when $Cost_{teeth} =$

$Cost_{non\text{-}teeth}$.

$$P(teeth \mid X) = P(non\text{-}teeth \mid X)$$

Note that $P(X \mid teeth)$, $P(X \mid non\text{-}teeth)$, $P(teeth)$ and $P(non\text{-}teeth)$ are constant. In general, $P(non\text{-}teeth)$ is larger than or equal to $P(teeth)$ in a dental image. According to Bayesian test for *minimum cost*, mistaking *teeth* as *non-teeth* is larger cost, i.e. $Cost_{teeth} > Cost_{non\text{-}teeth}$. Therefore, we select the cost.

Let $Cost_{non\text{-}teeth} *P(non\text{-}teeth) = Cost_{teeth} *P(teeth)$ in order to decrease the cost of mistaking *teeth* as *non-teeth*. So comparing $P(teeth \mid X)$ and $P(non\text{-}teeth \mid X)$ can be reduced to compare $P(X \mid teeth)$ and $P(X \mid non\text{-}teeth)$.

Using a Bayesian Decision Rule, we can select a threshold value t. In our experiments, we select t = 371. But we can catch most soft tissue regions in case (a) of Fig. 2.2.2 but not in case (b) of Fig. 2.2.2. Consequently, a dynamic threshold is the best solution. We decide to adopt dynamic threshold.
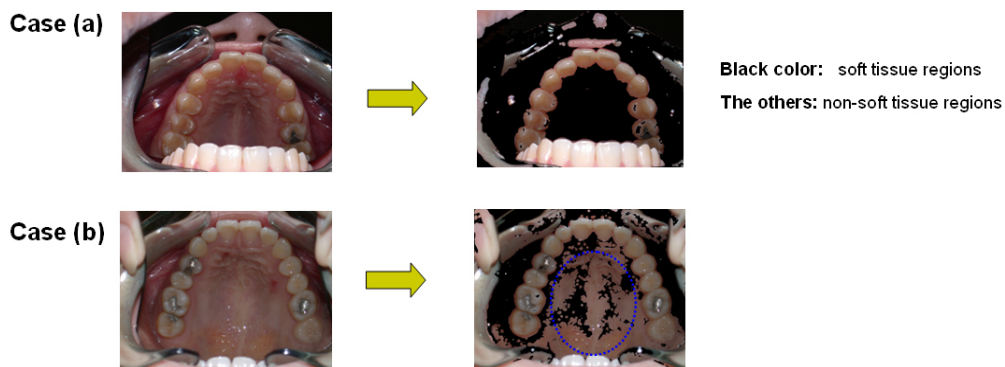

Fig. 2.2.3   A fixed threshold

(B) A dynamic threshold

Fig. 2.2.4   Close to the color of teeth

Fig. 2.2.5   Close to the color of soft tissue

The whole image color (hue value) may close to the color of soft tissue or to that of teeth. In Fig. 2.2.4, the whole image color (hue value) closes to the color of teeth. In Fig. 2.2.5, the whole image color (hue value) closes to the color of soft tissue. Since the hue in Fig. 2.2.4 is close to that of teeth, some soft tissue pixels are close to

the regions of teeth distribution in Fig. 2.2.6. Hence, some soft tissue pixels will be misclassified as teeth. So we can shift the threshold value right to include more soft tissue pixels which locate on near tooth distribution in Fig. 2.2.6.
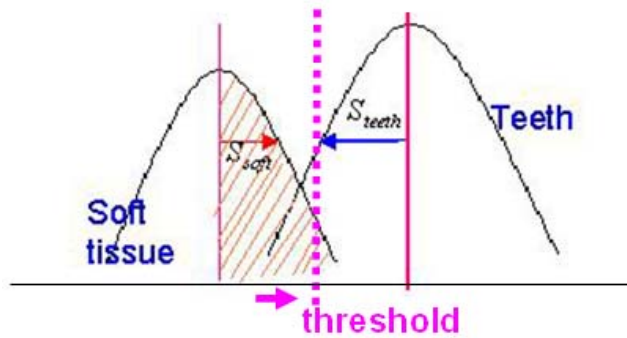

Fig. 2.2.6　Move threshold right

Since the hue in Fig. 2.2.5 is close to that of soft tissue, some teeth pixels are close to the regions of soft tissue distribution in Fig. 2.2.7. Hence, some teeth pixels will be misclassified as soft tissue. So we can shift the threshold value left to include more teeth pixels which locate on near soft tissue distribution in Fig. 2.2.7.
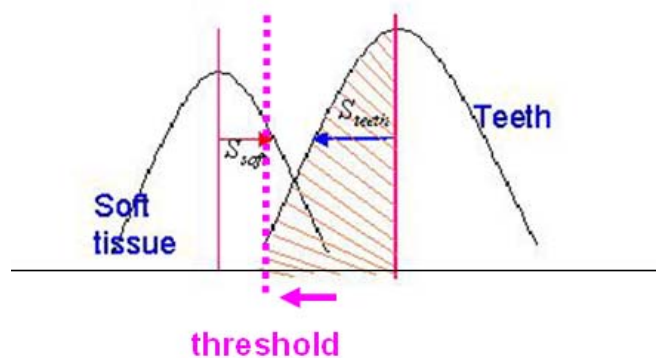

Fig. 2.2.7　Move threshold left

Now we know when to move right or left. Next step is how to move right or left. In general, we set a threshold value t in a normal distribution such as Fig. 2.2.8. If two normal distributions have the same variance, the distance from threshold to the mean of non-teeth is equal to the distance from threshold to the mean of teeth. They can be represented as:

$$\left| threshold - Mean_{non\text{-}teeth} \right| = \left| Mean_{teeth} - threshold \right| \quad \text{………… (Formula 2.2.1)}$$

So if the two normal distribution have different variance, we need normalize them as variance = 1 to satisfy the concept of the distance from threshold to the mean of non-teeth equal to the distance from threshold to the mean of teeth. Hence, we divide the deviation of non-teeth ($S_{non\text{-}teeth}$) and the deviation of teeth (S_{teeth}) at left side and right side of Formula 2.2.1 respectively. They can be calculated in a form of formula as follows:

$$\frac{\left| threshold - Mean_{non\text{-}teeth} \right|}{S_{non\text{-}teeth}} = \frac{\left| Mean_{teeth} - threshold \right|}{S_{teeth}} \quad \text{………… (Formula 2.2.2)}$$
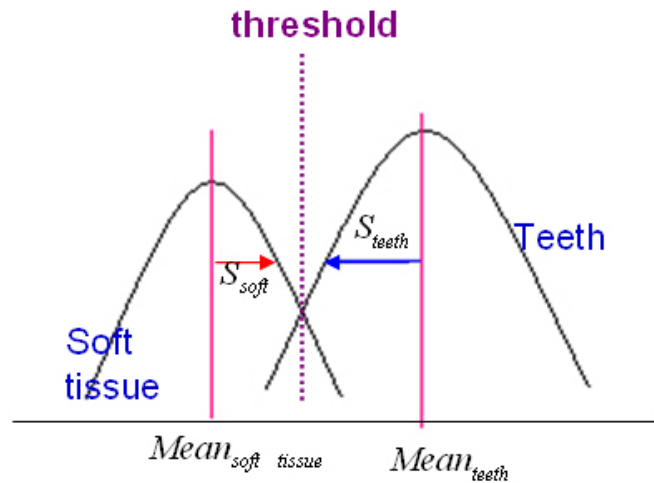
Fig. 2.2.8   General threshold

How to move threshold value right? We can multiply a constant α larger than 1 at right side of Formula 2.2.2. They can cause the effect of moving threshold right. The equation can be expressed as follows:

$$\frac{\left|threshold - Mean_{non\text{-}teeth}\right|}{S_{non\text{-}teeth}} = \frac{\alpha \times \left|Mean_{teeth} - threshold\right|}{S_{teeth}}, 0 < \alpha < 1$$
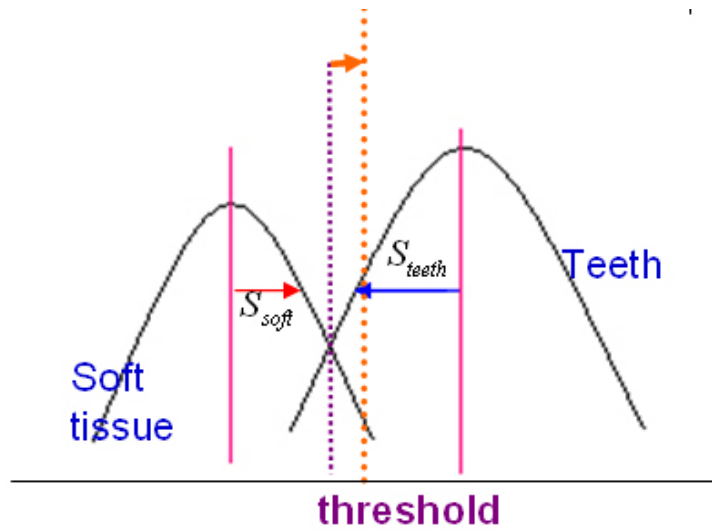
Formula 2.2.3

Fig. 2.2.9　Multiply $\alpha\,(\alpha>1)$ to move threshold

In the same way, how to move threshold value left? We can multiply a constant α less than 1 and larger than 0 at right side of Formula 2.2.2. They can cause the effect of moving threshold right. The equation can be expressed as follows:

$$\frac{\left|threshold - Mean_{non\text{-}teeth}\right|}{S_{non\text{-}teeth}} = \frac{\alpha \times \left|Mean_{teeth} - threshold\right|}{S_{teeth}}, 0 < \alpha < 1$$
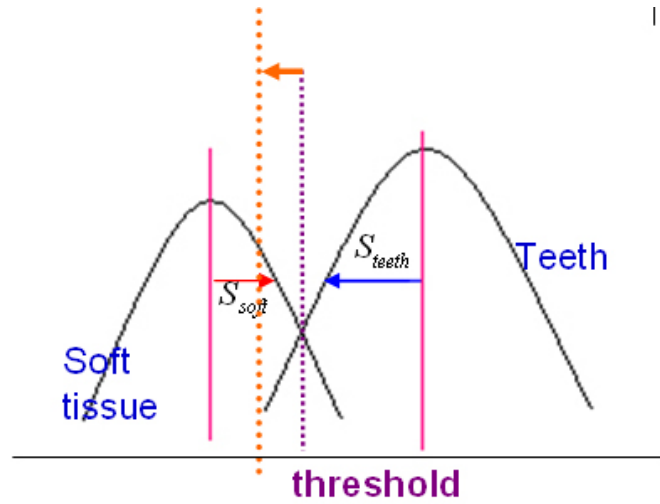
Formula 2.2.4

Fig. 2.2.10　Multiply α $(0<\alpha<1)$ to move threshold left

After realizing how to move threshold right or left, we introduce how to set a dynamic threshold value for each dental image. Soft tissue regions are one of major components in a dental image. So colors of soft tissue regions are enough weight to affect the mean of a whole image. Therefore, we can calculate the mean of a whole image, M_G, to represent the whole image color. And we obtain an average hue mean, m_1, from training images. If the hue mean of a whole image, M_G, is larger than m_1, the whole image color close to tooth distribution. If the hue mean of a whole image, M_G, is less than m_1, the whole image color close to soft tissue distribution. After obtaining M_G, we can decide α value. The value of α can be calculated as follows:

$$\begin{cases} \text{if } M_G > m_1 \Rightarrow \alpha = 1 + \frac{(M_G - m_1)}{d} \\ \text{if } M_G < m_1 \Rightarrow \alpha = \frac{1}{1 + \frac{(m_1 - M_G)}{d}} \end{cases}$$

d is a constant, where we set $d = 2$, $m_1 = 355$

Formula 2.2.5

26

d is a constant which decide the speed of moving threshold right or left. In our experiment, we set d = 2. After gaining the value of α, we can obtain the threshold value. We attain the threshold value by reducing from Formula 2.2.3 and Formula 2.2.4. The process of reducing from Formula 2.2.3 and Formula 2.2.4 are listed as follows:

$$\frac{\left|threshold - Mean_{non-teeth}\right|}{Deviation_{non-teeth}} = \frac{\alpha \times \left|Mean_{teeth} - threshold\right|}{Deviation_{teeth}}$$

$$\Rightarrow \frac{(threshold - Mean_{non-teeth})}{Deviation_{non-teeth}} = \frac{\alpha \times (Mean_{teeth} - threshold)}{Deviation_{teeth}}$$

$$\Rightarrow \textbf{threshold} = \frac{\alpha \times Mean_{teeth}Deviation_{non-teeth} + Mean_{non-teeth}Deviation_{teeth}}{\alpha \times Deviation_{non-teeth} + Deviation_{teeth}}$$

Formula 2.2.6

Then we can decide tooth regions and soft tissue regions. Our algorithm can be described as follows:

1. Calculate the hue mean M_G of the input image.

2. Decide α:

$$\begin{cases} \text{if } M_G > m_1 \Rightarrow \alpha = 1 + \frac{(M_G - m_1)}{d} \\ \text{if } M_G < m_1 \Rightarrow \alpha = \frac{1}{1 + \frac{(m_1 - M_G)}{d}} \end{cases}$$

d is a constant, where we set d = 2, m_1 = 355

3. Calculate threshold value:

$$\textbf{threshold} = \frac{\alpha \times Mean_{teeth}Deviation_{non-teeth} + Mean_{non-teeth}Deviation_{teeth}}{\alpha \times Deviation_{non-teeth} + Deviation_{teeth}}$$

27

4.   Tooth regions and soft tissue regions are decided as:

$$\begin{cases} \text{if } H(i,j) \geq \text{threshold, then assign } (i,j) \text{ to teeth} \\ \text{else assign to soft tissue} \end{cases}$$

or

if $I(i,j) \geq 160$, then assign (i,j) to teeth

if $I(i,j) \leq 48$, then assign (i,j) to non - teeth

After using dynamic threshold, we can obtain most soft tissue regions in images close to the color of teeth (in the case (b) of Fig. 2.2.11) or close to the color of soft tissue (in the case (a) of Fig. 2.2.11).
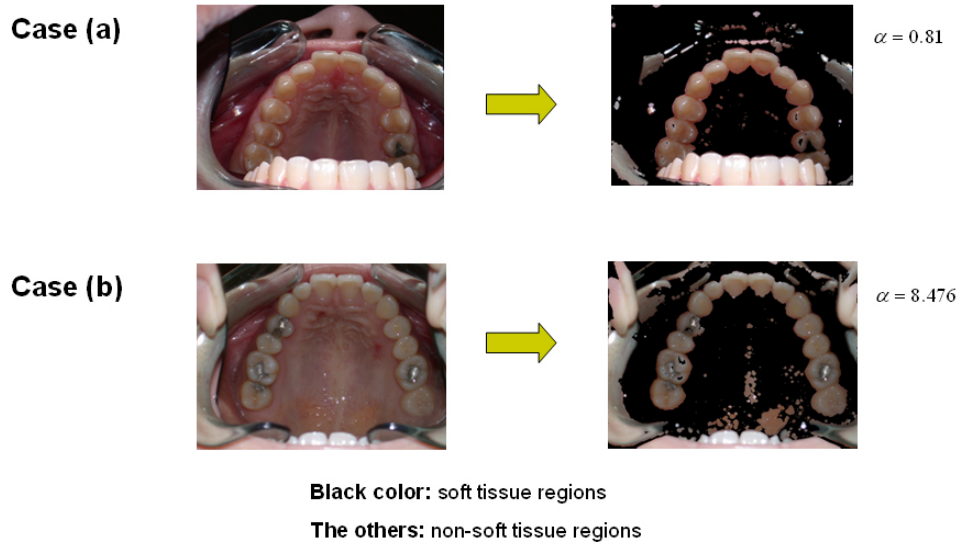

Fig. 2.2.11   Dynamic threshold

2.3 Extraction from Line-aligned Images

We use a lip retractor to expand the mouth. We can see that tooth regions are surrounded by soft tissue regions in Fig. 2.3.1. We employ the property to extract

tooth regions by removing non-tooth ones.

Fig. 2.3.1   Surrounded by soft tissue

We use the previous dynamic threshold to decide tooth regions and soft tissue regions. Then we use 3x3 windows to erase noise. The result is shown in Fig. 2.3.1.
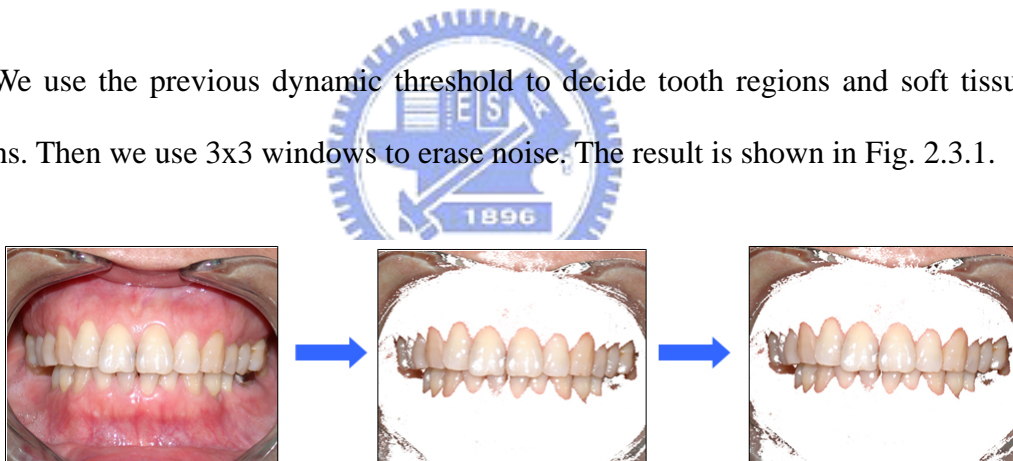

Fig. 2.3.2   Possible tooth regions

Since the tooth region is an isolated region surrounded by the soft tissue region, we can remove the connected-components that touch the image border. The result is displayed in Fig. 2.3.3.

Fig. 2.3.3 Remove regions touching the image

Region of upper teeth and that of lower teeth are the same connected component because upper maxilla and lower mandible are occlusive. After removing the connected-components that touch the image border, the connected component of upper teeth and lower teeth becomes the maximum one. Hence, we can obtain the tooth region by finding the maximum connected component. But we also find that some holes exist in tooth region. So we need fill holes. Which holes are needed to fill? We fill the connected components (F) which are not belonging to tooth region and are the first maximum connected components excluding tooth region. And those connected components (F) also need satisfy intensity larger than 48.

$$\text{if pixel}(x, y) \text{ of which value of } I > 48, \text{ then fill it.}$$

After filling holes, we can obtain the tooth region from a dental image. The result is revealed in Fig. 2.3.4.

Fig. 2.3.4   After filling holes

2.4 Extraction from Parabola-aligned Images

Some the lip retractor image will touch the teeth image in Fig. 2.4.1. If we use the method of 2.3 to exclude the connected-components that touch the image boundary, we will remove the tooth regions. That is, using the method of section 2.3 may be not perfect in parabola-aligned images. Therefore, we introduce position information to extract tooth regions.
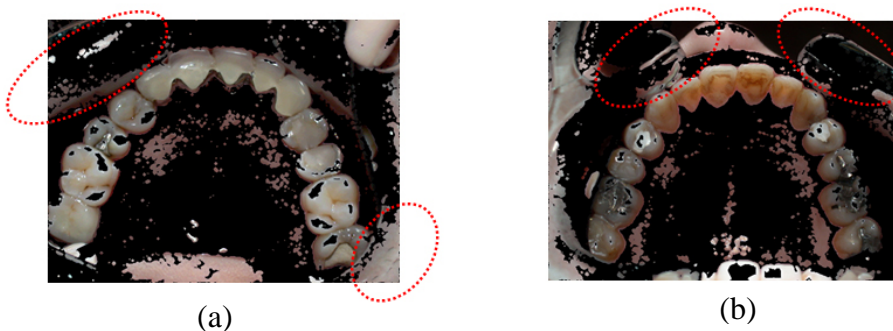

(a)   (b)

Fig. 2.4.1   Lip retractor images touch the teeth image

The position of each tooth in the images locates on a fixed range. When we collect diversity of samples enough to represent all position which tooth region appears or not, we can use position feature to exclude the regions where teeth do not appear. Our training samples are depicted in Fig. 2.4.2. We stack several images to count the number of appearance of teeth. When the number of appearance of teeth is 0, we think that the position is a region which teeth do not appear. We regard it as non-tooth region because teeth do not appear. Hence, position information can be defined as:

$$P_{(x,y)} = \begin{cases} 1, & \textit{if count number} > 0 \\ 0, & \textit{if count number} = 0 \end{cases}$$

$$\textit{where} \quad P_{(x,y)} \textit{ is the pixel locate on th pixe}(x,y)$$

We normalize the number of appearance of teeth to 1 to 255 and draw the map of the teeth appearance frequencies by the gray level of this position = (255 – the normalized number of appearance of teeth). The map of the teeth appearance frequencies is shown in Fig. 2.4.3. The darker color points represent that the frequency of teeth appearance is higher in Fig. 2.4.3.

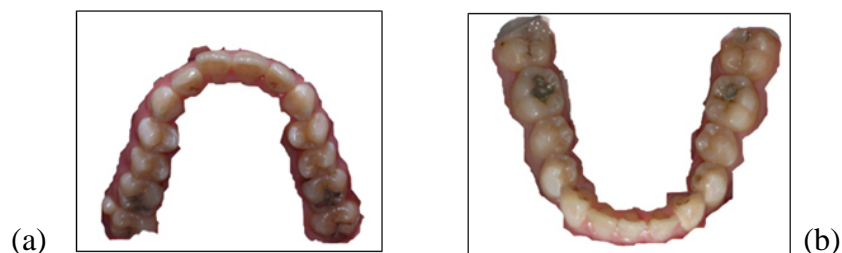(a)   (b)
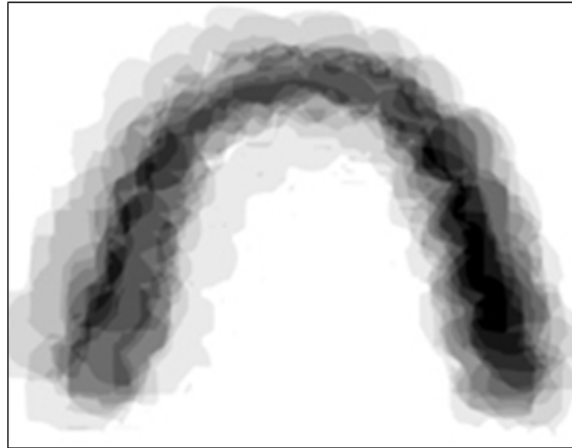
Fig. 2.4.2   Position feature

Fig. 2.4.3   The map of the teeth appearance

We use position feature to exclude regions which teeth never appear in and then apply the dynamic threshold method of section 2.2 to decide tooth regions and soft tissue regions. We use 3x3 windows to erase noise. The result is shown in Fig. 2.4.4.
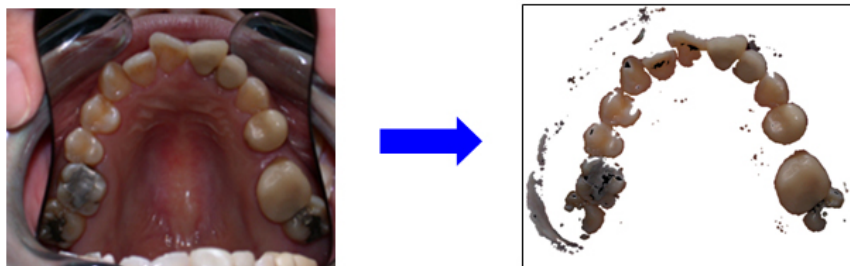

Fig. 2.4.4   Possible tooth regions

Next step, we want to remove non-tooth regions. Because we are not sure that select a fixed constant to m precisely such that the all first m largest connected components must be tooth regions and not be non-tooth regions. So we just select a value to include all possible tooth regions. First, we select the first n largest connected

components C_1,C_2, ……, C_n where we select n=10. The result is shown in Fig. 2.4.5.

Fig. 2.4.5   The first largest n components

Tooth regions align the form of parabola. We can use this property to project the first n largest components into a parabola where starts from x_1 to x_2 in the x-axis. They will fill the axis of parabola. Second, we project the first n largest components $C_1, C_2, \ldots\ldots, C_n$ into a parabola in Fig. 2.4.6. The project components in parabola axis are called $P_1, P_2, \ldots\ldots, P_n$ in sequence, i.e.

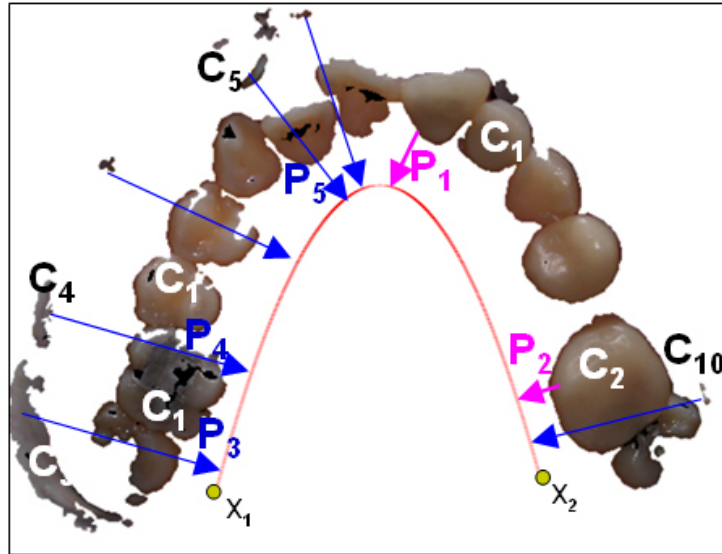$$P_1 = project(C_1), P_2 = project(C_2), \ldots\ldots, P_n = project(C_n)$$

34

Fig. 2.4.6　Project the first largest n components into a parabola

We exclude redundant components which can be represented by another project component in parabola axis. Third, we find components excluding redundant components. They can be selected by finding the set B as follows:

$$P_1 = project(C_1), P_2 = project(C_2), \ldots\ldots, P_n = project(C_n)$$
$$A = \{P_i\}_{,i=1,2,3\ldots.n}$$
$$B = \{a_i \mid a_i \cap a_j = \Phi, a_i \in A\}_{,\, i=1,2,3\ldots n,\, j=1,2,3\ldots n}$$

Hence, the set B is tooth regions. We mark a pixel as tooth regions if it belongs to B, i.e.

$$TeethRegion(x, y) = \begin{cases} 1, & if\,(x, y) \in B \\ 0, & if\,(x, y) \notin B \end{cases}$$
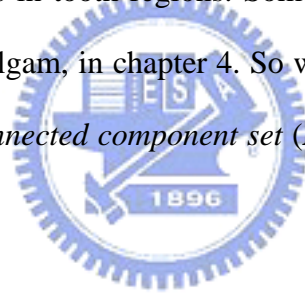$$where\ (x, y)\ is\ the\ pixel\ locate\ on\ pixel(x,y)$$

The result is shown in Fig. 2.4.7.

Fig. 2.4.7   Tooth regions

But there are some holes in tooth regions. Some may be amalgam regions. We want to detect the status, amalgam, in chapter 4. So we need the step of filling holes. We can find *the maximum connected component set* (**F**) from the set not belonging to the set **B**.

Then the other components not belonging to the set **B** and exclude the set **F** are holes we need fill. We can describe the steps as the follow formula:

$$FillRegion(x, y) = \begin{cases} 1, & if\ (x,y) \notin B \bigcap (x,y) \notin F \\ 0, & if\ (x,y) \in B \end{cases}$$

where   FillRegion(*x, y*) is the pixel locate on the pixel(*x,y*)

The result is shown in Fig. 2.4.8.

Fig. 2.4.8   Tooth regions after filling holes