CHAPTER 5

TEXTURE BASED APPROACH OF VICTIM IDENTIFICATION WITH TEETH CLASSIFICATION AND A COMPARATIVE ANALYSIS

5.1 INTRODUCTION

The task of victim identification is achieved by both dental radiographs and photographs. Chapter 1 explains the usage of radiographs with fast connected component analysis. In order to improve the hit rate percentage of victim identification, the dental image segmentation is attained with contour based technique in the chapter 2. The presence of missing tooth in both ante mortem and post mortem images is also considered in that chapter. A slightly variant approach of chapter 2 is presented in chapter 3 with skeleton method for dental shape extraction along with teeth numbering in order to reduce the database search time. The applicability of the algorithms developed in chapter 2 and chapter 3 are tested with photographic images also. After passing chapter 3, it is observed that teeth numbering will reduce search time to some extent only. So, combining teeth classification with teeth numbering will reduce the database search time still better. In this chapter, texture based dental shape information and shape matching are tried. The main goal of this chapter is to obtain efficient candidate matching process by combining teeth classification with teeth numbering along with fast connected
component contour, skeletal and texture information for both shape extraction and matching.

5.2 LITERATURE REVIEW

5.2.1 Support Vector Machine (SVM) for classification

Image classification is one important branch of artificial intelligence. The term image classification refers to the labeling of images into one of a number of predefined categories. SVM is a learning tool originated in modern statistical learning theory (Vapnik 1998). It gives better performance in classification of image than other data classification algorithms. SVM can generalize well on difficult image classification problems by using high dimensional histograms (Olivier Chapelle et al, 1999). In recent years, SVM learning has found a wide range of real world applications including handwritten digit recognition (Scholkopf et al 1997), face detection in images (Osuna et al 1997), object recognition (Pontil & Verri 1998), text categorization (Joachims 1999) and speaker identification (Wan & Campbell 2000).

The SVM classifier can be used to detect cell nuclei for automated microscopy with laplacian edges as features and are explained by Ji Wan Han (2010). A binary linear SVM using the skew adjusted relative length/width ratios of both teeth, pulp and crown size as features are used by Lin et al (2010) to classify each tooth as molar or premolar. The missing teeth identification can also be obtained by Faraein Aeini & Fariborz Mahmoudi (2010) along with teeth classification using linear SVM by using Mesiodistal neck as the feature. Lee et al (2012), have introduced a hierarchical SVM, which selects a class by training a binary classifier at each node in a hierarchy, thus allowing each classifier to use a class specific quasi-optimal feature set. This logic can be useful for differentiating diffuse interstitial lung
diseases for computer aided quantification. Chang et al (2013) have used SVM for classifying different disease patterns in lung disease and compared the classification accuracy against Bayesian classifier.

5.2.2 Texture based shape extraction

Analysis of dental X-ray images has some difficulty in comparison with other medical images, which makes segmentation a more challenging process. The difficulties are like: inclusion of artifacts, impacted teeth, variations of teeth, space between missing tooth, and also problems during processing of images. Due to these problems, still finding the accurate and proper method in the segmentation of dental X-ray images is a challenging process. Nonetheless, many surveys on medical image processing have been published in different journals, but none of them have focused on dental X-ray images. Texture plays an important role in human vision and is important in image segmentation and classification. To access images based on their contents, several features such as color, shape and texture are extracted from them. The gold standard method for differentiating benign from malignant micro calcifications is biopsy and which is invasive. Hamid Soltanian Zadeh et al (2001) have proposed a method to reduce rate of biopsies with negative results. Martin Leonard Tangel et al (2012) have proposed a method, which is more accurate than that obtained by employing the Otsu method, and it is robust against inconsistent contrast, uneven exposure and pixel’s noise of the radiograph.

In teeth-related radiographic research, the information of teeth shape is the most critical factor for achieving highly automated diagnosis. Therefore, accurate segmentation is an essential but difficult task due to low contrast and uneven exposure of the dental X-ray images. Abdolvahab Ehsani Rad et al (2013) have presented a novel scheme to automatically segment teeth by using texture characteristics instead of primitive intensity or edge used in the previous research works. Texture based analysis is one of the
region based image segmentation approaches (Narkhede 2013). Compared to edge detection method, segmentation algorithms based on region are immune to noise (Zhang et al 2008, Kang et al 2009).

5.3 ISSUES AND PROBLEM FORMULATION

The various issues existing in the literature for victim identification using dental images are addressed in the previous chapters. The proposed solutions for few of the issues are also explained in the earlier chapters. One of the issues like database search time reduction is handled in the previous chapter using teeth numbering and is further improved by including teeth classification in this chapter.

The hit rate improvement using some reliable and efficient segmentation and matching algorithm is another issue to notice. The segmentation and matching are handled here by using texture information rather than the edge details as used in conventional methods.

The objective of this chapter is to model an automatic victim identification algorithm initially by performing numbering and classification of teeth and then observing texture based shape extraction, matching and making a comparative analysis over contour, skeleton and connected component based approaches finally.

Figure 5.1 Layout of the proposed approach
5.4 PROPOSED METHODOLOGY

The layout of this chapter is shown in Figure 5.1. The pipeline of this method framed to assist Forensic experts is shown in Figure 5.2. Input images taken for analysis include dental radiographs and photographs. Then, teeth isolation is made with the spline function followed by integral intensity projection logic. Subsequently, missing teeth detection is carried out and shape extraction is performed using texture, contour and skeleton. Shape matching is obtained by Gray Level Co-occurrence Matrix (GLCM), angle and distance approach and skeleton parameters.

![Figure 5.2 Pipeline of the proposed algorithm](image)

### 5.4.1 Spline Isolation and Missing Tooth Identification

The input dental images captured are preprocessed initially to obtain it in a feasible form for carrying out further analysis. The preprocessing is performed using the combination of homomorphic filter with
butterworth band pass filter (Lin et al 2010) as explained in the previous chapter. After this processing, the teeth in the image are isolated and are tested for missing tooth.

5.4.1.1 Spline isolation

For teeth isolation, integral intensity projection logic is adapted in chapter1. It may not be a feasible, if the teeth in the dental image are with large skew. In such cases, the spline function (de Boor 2001) is used to get curved lines as explained in chapter3. The control points for tracing the spline curve are obtained by the integral intensity projection plot by using the Equations (3.2), (3.3) and (3.4).

5.4.1.2 Missing teeth Detection

While designing ADIS, care should be taken to observe missing tooth in both AM and PM dental records. If there is a missing tooth, then matching may not be made with those images. Hence, there should be some algorithm to identify and measure the missing tooth region. It is attained here by following the logic given in chapter3.

5.4.2 Classification and Numbering

After teeth isolation from the previous step, the individual tooth obtained is given as input for the classifier. Teeth classification is carried out by extracting the features initially and then it is applied to the SVM classifier for categorizing the tooth as molar, premolar or canine in case of radiographs and central or lateral incisor in case of photographs (Faraein Aeini & Fariborz Mahmoudi 2010).

5.4.2.1 Classification

Binary or two class Support Vector Machine is used as a classifier tool as suggested by Lin et al (2010) to categorize the tooth as molar and
premolar in case of radiographic images and lateral or central incisor for photographic images. Then, binary SVM is used in cascaded combination to behave like a multi-class SVM in order to classify another radiographic tooth like canine. Teeth classification involves feature extraction and classifier stages.

**Feature Extraction**

The features desired for teeth classification are extracted in four different forms like Projected Principal Edge Distribution (PPED) vectors (Banumathi et al 2009), signatures, geometric features and regional descriptors.

PPED feature extraction tries to capture the information content of a tooth by modeling its edge distribution along different principal directions or orientations. The four principal directions are horizontal (H), Vertical (V), +45 degree (clockwise) and -45 degree (anti-clockwise). Since two-dimensional edge information is reduced to a feature vector by projecting edge flags to the principal directions, it is named as Projected Principal Edge Distribution. The isolated tooth image is subjected to filtering operation for edge detection in the principal directions namely, horizontal, vertical, +45 degree and -45 degree. The maximum edge intensity is compared with the threshold value to detect the presence of edge. This eliminates the effect of noise. In order to determine the threshold value for edge detection, all the absolute value differences between two neighboring pixels are calculated in both horizontal and vertical directions and the median is taken as the threshold. The filtering kernels used for edge detection are given in Figure 5.3

Shape signature is the next feature considered here. It is a 1D representation of 2D boundary. For finding out the signature, centroid is
calculated. Then, the centroid distance function of the tooth boundary points from the centroid \((x_c, y_c)\) of the tooth shape is obtained by:

\[
r(t) = \left( [x(t) - x_c]^2 + [y(t) - y_c]^2 \right)^{1/2}
\]  

\[
x_c = \frac{1}{N} \sum_{t=0}^{N-1} x(t) \quad \& \quad y_c = \frac{1}{N} \sum_{t=0}^{N-1} y(t)
\]  

where \(x(t)\) is the row pixels along the boundary, \(y(t)\) is the column boundary pixels and \(N\) is the maximum size of the image.

\begin{figure}[h]
\begin{center}
\begin{tabular}{cccc}
0 & 0 & 0 & 0 \\
1 & 1 & 1 & 1 \\
0 & 0 & 0 & 0 \\
-1 & -1 & -1 & -1 \\
0 & 0 & 0 & 0
\end{tabular} &
\begin{tabular}{cccc}
0 & 1 & 0 & -1 \\
0 & 1 & 0 & -1 \\
0 & 1 & 0 & -1 \\
0 & 1 & 0 & -1 \\
0 & 1 & 0 & -1
\end{tabular}
\end{center}
\caption{Kernels used for PPED}
\end{figure}

The additional features are derived from the geometrical view of the teeth. Each tooth consists of two major parts like crown and root. The centroid of each tooth will locate crown center. From the crown center the width of two extreme corners are obtained as W1 and W2. The parameter h1 is the height of the root region and h2 is the crown region. These parameters are shown in Figure 5.4.
Figure 5.4 Geometric properties

The classification accuracy is improved further by considering the total height and width of the tooth as given:

$$W = W_1 + W_2$$

$$H = h_1 + h_2$$

In many cases, teeth may appear with skew due to shooting, injury or poorly aligned and when taking the radiograph, some root areas may not appear as well. Thus, in addition to these features, some more regional descriptors like Total Area (TA), Filled Area (FA) and Equivalent Diameter (ED) are also observed as features for SVM.

SVM Classifier

Jacob et al (2004) have proposed SVM as an attractive and alternative method for the classification of medical images. The appeal of SVM is based on their strong connection to the underlying statistical learning theory, with key features such as, the use of kernels, the use of local minima, the sparseness of the solution and optimizing the margin of various classes. This approach seeks to find an optimal hyper plane between classes, by
choosing the training vectors that lie at the edge of the class distribution. The training vectors far away from the hyper plane are effectively discarded. Thus, not only an optimal hyper plane is fitted, but the approach will yield high accuracy using less training sets. The optimization here uses convex quadratic programming where solutions are not only explicitly defined, but are unique and sparse. Once a suitable kernel for SVM is chosen, the structure of support vector classifier is data driven and is automatically determined (Jian-xiong Dong et al 2005).

The formulation of SVM learning is based on the principle of structural risk minimization. Instead of minimizing an objective function based on the training samples, the SVM attempts to minimize a bound on the generalization error (i.e., the error made by the learning machine on test data not used during training). As a result, SVM tends to perform well, when applied to data outside the training set. It has been reported that SVM-based approaches are able to significantly outperform competing methods in many applications (El-Naqa et al 2002). SVM achieves this advantage by focusing on the training samples that are most difficult to classify. From the Baye’s classifier to neural networks, there are many possible choices for appropriate classification. Among these, support vector machines would appear to be a good candidate because of their ability to generalize in high-dimensional spaces.

**Binary Support Vector Machine**

Binary SVM is used as a classifier tool to categorize the tooth as molar or premolar in case of radiographic images. The basic idea behind SVM is transferring the data into higher dimensional space and finding the optimal hyperplane with maximal separation between classes. By assuming the data as linearly separable, the hyperplane of SVM has the form of \( w \cdot p + b = 0 \), where \( w \) is the normal to the hyperplane and \( \frac{b}{\|w\|} \) is the perpendicular distance between the origin and the hyperplane (Lin et al 2010).
Consider some randomly selected data from the whole data set as the training set for finding the optimal hyperplane $w^* \cdot p + b^* = 0$, which is as far as possible from the closest members of both classes. Few of the training vectors called support vectors and they will fall on either side of the two planes $B_1 : w \cdot p + b = 1$ and $B_2 : w \cdot p + b = -1$. Thus, the hyperplane $w^* \cdot p + b^* = 0$ is called the decision boundary of the binary classifier. Each training data are denoted by a tuple $(p_i, q_i)$, where $p$ corresponds to the feature vectors and $q$ corresponds to the class label (i.e.) $q \in \{1, -1\}$. The optimal $w^*$ and $b^*$ of binary SVM model can be calculated as:

$$w^* = \sum_{i=1}^{M} \alpha_i q_i P_i$$

(5.3)

$$b^* = \frac{1}{N} \sum_{i \in S} \left( q_i - \sum_{m \in S} \alpha_m q_m P_m \cdot P_i \right)$$

(5.4)

where, $\alpha$ is the Lagrange multiplier such that $\sum_{i=1}^{M} \alpha_i - (1/2) \alpha^T B \alpha$ is maximized, subject to the constraints $\alpha_i \geq 0 \forall i$ and $\sum_{i=1}^{M} \alpha_i q_i = 0$, $B$ is a matrix with $B_{ij} = q_i q_j P_i \cdot P_j$ and $S$ is the set of support vectors whose $\alpha_i > 0$. The following signum function is used to group the test data into either of the class after constructing the decision hyperplane: $q' = \text{sgn}(w^* \cdot p' - b^*)$. It is observed that, if $q > 0$, it belongs to molar otherwise premolar tooth.

**Multi-class Support Vector Machine**

Support Vector Machines are originally designed for binary classification. Effectively extending this for multi-class classification is still an on-going research. Currently, there are two types of approaches for multi-class SVM. One method is by constructing and combining several binary classifiers, while the other is by directly considering all data in one optimization formulation. In general, it is computationally expensive to solve
a multi-class problem than a binary problem with the same number of data (Chih-Wei Hsu & Chih-Jen Lin 2002). In this chapter, three classes are handled using two binary classifiers as shown in the Figure 5.5. Here, X, Y and Z refer to molar, premolar and canine respectively. In general, it requires (M-1) binary classifiers, if M classes have been considered.

![Flowchart for classification of three teeth using Linear SVM](image)

**Figure 5.5 Classification of three teeth using Linear SVM**

### 5.4.2.2 Numbering

In view of reducing the database search time, teeth numbering is performed. Numbering of teeth along with teeth classification will yield better results. For teeth numbering, template matching process is used followed by universal teeth numbering.

### 5.4.3 Tooth Shape Extraction

Tooth shape information is a desirable feature, while going for individual identification. Contour and skeleton are extracted then to represent
the shape of the tooth. Texture information is also observed to attain the shape
details of teeth additionally.

5.4.3.1 Contour extraction

Contour of entire teeth pattern and an individual tooth are extracted
using Selective Binary Gaussian Filtering and Regularized Level set
(SBGFRLS) method (Kaihua Zhang et al 2010). It uses a new region-based
Signed Pressure Force (SPF) function, which can efficiently stop the contours
at weak or blurred edges as explained in chapter 3.

5.4.3.2 Skeleton extraction

Skeleton is another means of shape extraction as detailed in
chapter-4. Medial axis counterparts of individual tooth are extracted (Saeed
2001) in addition to the contour, in order to compare and contrast for finding
better suited algorithm.

5.4.3.3 Texture information

Texture is a repeating pattern of local variations in image intensity.
Texture Analysis is carried out to quantify the individual tooth texture. One of
the statistical methods extensively used is Gray Level Co-occurrence Matrix
(GLCM). GLCM contains information about the position of pixels having
similar gray level values (Weszka 1976). GLCM is defined by first
specifying a displacement vector \( d = (d_x, d_y) \) and counting all pairs of pixels
separated by \( d \) having gray levels \( i \) and \( j \). The GLCM is denoted as \( P \),
which is given as:

\[
P_d[i,j] = n_{i,j}
\]

where, \( n_{i,j} \) is the number of occurrences of the pixel values lying at a distance
\( d \) with co-ordinates \((i, j)\) in the image.
5.4.4 Shape Matching

Like shape extraction, shape matching is the next desirable factor. Shape matching is one of the fundamental problems in computer vision. In this work, it is achieved with the angle and distance measures as given in Figure 5.6 using skeletal and GLCM parameters.

5.4.4.1 Contour based matching

The ante-mortem dental records might have captured too earlier than the post mortem images. Hence, the viewing angle might be differing in both the dental records. So, there is a necessity of applying a rigid transformation to both AM and PM images before finding the distance. The Matching Distance (MD) obtained can be improved by the rigid transformation (Anil K Jain et al 2004). Similarity of query and the data base images can be observed by using the edge strength. The probability $p(e)$ of an edge in the query image close to that of the database image is calculated as:

$$p(e) = \frac{1}{2} + \frac{1}{C_k} \sum_{q \in N(e)} \tilde{K}(q - e, h, n) E_q(c + q) \hat{G}_o(e) \hat{G}_o(c + q)$$  \hspace{1cm} (5.6)
where,

\[ C_k = 2 \sum_{q \in N(e)} \tilde{K}(q - e, h, n) \]  

(5.7)

and \( \tilde{K} \) is the kernel function with the adjustable parameter \( h \) is given as:

\[
\tilde{K}(x, h, n) = \begin{cases} 
K\left( \frac{||x||}{h} \right) & ||x|| \leq n \\
0 & \text{otherwise} 
\end{cases}
\]  

(5.8)

The size of query image is \( n \times n \). \( E_q \) is the edge gradient of query image, \( \hat{G}_d \) and \( \hat{G}_q \) are the mapped edge gradients of the database and query image respectively and \( x \) is the pixel element of an image. Overall similarity is the mean probability, which is defined as follows:

\[
S = \frac{1}{|L_d|} \sum_{e \in L_d} p(e) 
\]  

(5.9)

\( L_d \) is the edge pixel list of database image. Euclidean distance measure is then used to find the distance of database and query image based on the similarity probability.

5.4.4.2 Skeletal based matching

In conventional methods, computing a set of skeletal nodes, connecting the nodes into a graph, indexing into a database and verification with one or more objects are followed (Rockett 2005). In this chapter, additional parameters are observed for skeleton matching. They are: the centroid, distance between the skeleton end point from the origin, the length of the skeleton and angle of skeleton end point to the reference point. The angle and ED are obtained using Equations (4.13) and (2.20) respectively.
5.4.4.3 Texture based matching

Texture is an important attribute of an image and a useful measure for image matching and retrieval. The notable GLCM parameters such as contrast, correlation, energy and homogeneity are observed (Haralick 1981) for teeth matching by using the following relations.

\[ \text{Contrast} = \sum_{i,j} |i - j|^3 P(i, j) \]  

(5.10)

\[ \text{Correlation} = \sum_{i,j} \frac{(i - \mu_i)(j - \mu_j)P(i, j)}{\sigma_i \sigma_j} \]  

(5.11)

\[ \text{Energy} = \sum_{i,j} P(i, j)^2 \]  

(5.12)

\[ \text{Homogeneity} = \sum_{i,j} \frac{P(i, j)}{1 + |i - j|} \]  

(5.13)

where, \( \mu_i \) and \( \mu_j \) correspond to mean value of row and column respectively and \( \sigma_i, \sigma_j \) are the corresponding standard deviation.

5.5 RESULTS AND DISCUSSION

In this section, experimental results of this algorithm are presented. For radiographs, a database collected from Madurai Digital Dental X-Ray is used, which includes periapical, panoramic and bitewing images. The photographic images are captured among the age group of 22 to 65 using cyber-shot DSC W690 camera with 16 Mega pixels resolution. Figure 5.7 and Figure 5.8 show the sample radiographic and photographic database respectively. This algorithm is evaluated with a database of 104 dental images which include both radiographs and photographs. Few of the radiographic images are considered with missing tooth as well as dental works such as
crown mineralization, dental implants and crown filling. Out of the 104 images, 62 are radiographs and 42 are photographs. The algorithm is

![Sample radiographic images](image)

**Figure 5.7 Sample radiographic images**

Implemented in MATLAB R2010b, using a Pentium IV CPU (3.00 GHz-Dual Core) on a Microsoft Windows XP environment. Victim identification can be made perfect by considering single tooth separately rather than the whole image by itself. Hence, spline function is used here to isolate each and every tooth separately. The results are shown in Figure 5.10. Figure 5.9 (a) is the isolated panoramic radiograph. Figure 5.9 (b) is the bitewing radiograph with a missing tooth. Since the missing tooth region is a wide slit with less intensity, it is isolated using spline function itself. Figure 5.9(c) is the photographic image with two missing tooth regions.
Figure 5.8 Sample photographic images

Figure 5.9  (a) Isolated Panoramic radiograph (b) Bitewing Radiograph (c) Photograph with missing teeth

It is noticeable that out of the two slits, one region is isolated whereas the other is not using spline function. Hence, there is a necessity of an efficient missing tooth detection algorithm. As explained in section-5.4.1.2, these regions can be identified and several useful measures such as its length and width can be observed. Figure 5.11 demonstrates the results of missing tooth cases. Figure 5.10 (a) is a periapical radiograph with two slits. These slits are identified exactly by this algorithm and the measures are noted. The same algorithm works well for photographic images also. The two missing tooth regions are identified exactly by this algorithm and are exposed
in Figure 5.10 (b). Another photographic image with two consecutive slits is shown in Figure 5.10(c).

![Figure 5.10](image)

**Figure 5.10  Missing tooth calculation and the parameters (a) Periapical radiograph  (b) &(c) photographic cases**

Since this work employs single tooth alone for shape extraction and matching purposes, individual tooth is segregated and a database is created. It includes 100 premolars, 120 molars, 50 canine, 80 central incisors and 70 lateral incisors. A sample of this database with few molar, premolar teeth of radiographs and few lateral and central incisors in case of photographs are shown in Figure 5.11. For radiographic bitewing images, according to the two standard teeth patterns (Lin et al 2010 ) a majority of either molar or premolar and a minority of canine teeth will be presented for experimentation.
Figure 5.11 Sample database - molar, premolar of radiograph and incisors of photographic images

The features of the individual tooth are extracted to provide input to the Support Vector Machine (SVM). The feature extraction is performed here in three ways. The PPED vectors extracted for a sample molar and premolar teeth are shown in Figures 5.12 and 5.13 respectively. It seems to be unique for all the teeth.

Figure 5.12 Feature extraction using PPED (a) Input Molar (b) Horizontal edge flag (c) Vertical edge flag (d) +45 Degree edge flag (e) -45 degree edge flag (f) PPED vector
Figure 5.13 Feature extraction using PPED a) Input Premolar (b) Horizontal edge flag (c) Vertical edge flag (d) +45 Degree edge flag (e) -45 degree edge flag (f) PPED vector

The edge based features are generated in all the four principal directions like horizontal, vertical, +45 degree and -45 degree as shown in the above Figures in order to plot the PPED vector. In connection with this, geometric features are also extracted to make the classification further more efficient. The generated features for few sample images are shown in Figure 5.14.

Figure 5.14 Geometric features of sample images (a) Premolar of Mandible (b) Molar of Mandible (c) Premolar of Maxilla
The width parameters W1, W2 and the height parameters h1, h2 are seen to be different almost for all the images in the database. Along with these parameters, by approximating the tooth as an elliptical region, some simple descriptors like filled area, total area and the equivalent diameter of these teeth are also observed to get fruitful classification results. The observed features for some images Tooth1, Tooth2, Tooth3, Tooth4 and Tooth5 are shown in Table 5.1. In this table, W1 and W2 refer to width1 and width2 and h1 and h2 refer to height1 and height2 respectively. TA denotes Total Area, FA is Filled Area and ED refers to Equivalent Diameter.

<table>
<thead>
<tr>
<th>Images</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>W1</td>
</tr>
<tr>
<td>Tooth1</td>
<td>28</td>
</tr>
<tr>
<td>Tooth2</td>
<td>25</td>
</tr>
<tr>
<td>Tooth3</td>
<td>24</td>
</tr>
<tr>
<td>Tooth4</td>
<td>27</td>
</tr>
<tr>
<td>Tooth5</td>
<td>36</td>
</tr>
</tbody>
</table>
The SVM is trained with the database of 320 individual teeth and 160 teeth are used for testing. The features like PPED vectors, geometric properties and simple descriptors are combined together and fed as inputs to the binary SVM. The hyperplane separation of a sample premolar tooth is shown in Figure 5.15. Similar output for molar tooth is revealed in Figure 5.16. Based on the results obtained from classification, the teeth are categorized as given in Figure 5.18. This classification results will be helpful in victim identification system, as it needs to match the particular tooth with the corresponding tooth alone in the database. Thus, it reduces the search space in turn the search time.

![Figure 5.15 Hyperplane separation of a Premolar tooth](image)

**Figure 5.15 Hyperplane separation of a Premolar tooth**
Figure 5.16 Hyperplane separation of a Molar tooth

It is understood from Vijayakumari et al (2013) that individual tooth matching will yield better results than matching either the whole image or the mandible or maxilla. The classified single molar, premolar, canine, central incisor and lateral incisor teeth are shown in Figure 5.17.

Figure 5.17 Classified individual teeth
Figure 5.18 (a) - (g) show the resultant images obtained for the template matching and numbering for the radiographs and photographs.

Figure 5.19 (a) illustrates the classification and numbering results obtained for a radiographic image taken from the left side of the face. It involves the teeth sequence of ‘PPMM’ in both maxilla and mandible regions. Figure 5.19 (b) exemplifies the results for the image taken from the right side of the face. It consists of ‘MMPP’ teeth sequence. Figure 5.19(c) is an example for photographic case. For experimental purpose, photographic image with clear view of both mandible and maxilla has been taken. While in practical situation, the photos taken from family albums consist mainly of the maxilla with central and lateral incisors and with the rare occurrence of mandible teeth. Hence, in photographic images, it is enough to cover four middle teeth on both the jaws. After numbering and classification, the database is alienated into molar, premolar and canine category for radiographic images and central and lateral incisors separately for photographic images. It makes a healthy environment for decision making and reduces the computational time.

![Figure 5.18](image_url)

**Figure 5.18** Results of Numbering (a), (e) – Template (b), (c), (f) – Template matched output(d), (g) – Numbering output
The classification is further extended by using rotational invariant signature, another feature in addition to the PPED and geometrical features. Three teeth in radiographic images are classified using multi-class SVM in terms of binary SVM. The results obtained for multi-class SVM are shown in the Table 5.2. It is observed from the table that the PPED and signature seem to be unique for different teeth. Additionally, the geometrical information W/H is also observed and which aids for useful classification results. The Table 5.2 shows a sample tooth for each category like panoramic, photographic and bitewing. The classification is initially tried using binary SVM. It yields better results for two teeth category like M and P for radiographs and CI and LI for photographs. In radiographs, an additional tooth category like canine is also added.

![Figure 5.19](image)

**Figure 5.19** Results of numbering and classification for radiograph and photograph (a) Radiograph taken from left side (b) Radiograph taken from right side (c) Photograph
Table 5.2 Features extracted and classified teeth

<table>
<thead>
<tr>
<th>Images (Tooth from)</th>
<th>Panoramic X-ray</th>
<th>Photograph</th>
<th>Bitewing X-ray</th>
</tr>
</thead>
<tbody>
<tr>
<td>PPED vectors</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Signature</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Geometrical features</td>
<td>36/101</td>
<td>49/70</td>
<td>55/95</td>
</tr>
<tr>
<td>W/H</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Classified Teeth</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The features used for linear SVM are considered to train and test the Multi-class SVM. While classifying, it is observed that the features of premolar and canine are closely related particularly, the geometrical feature. Hence, the mis-classification rate is more in case of these teeth. Mis-classification occurs rarely in premolar and molar teeth of panoramic images. In case of
bitewing radiographs, it is less pronounced because the teeth anatomy is very clear.

The shape matching is performed using contour, skeleton and texture information. Contour and skeleton extraction are carried out in chapter3 and chapter4 respectively. In this chapter, the texture information is also extracted to compare and contrast the proposed approaches. The contours of each and every tooth in both AM and PM records are obtained using SBGFRLS method. Similarly, the skeletons are traced based on iterative thinning process.

After getting contours and skeleton, the matching is made in two ways. First, pixel by pixel distance between both the query and the database images is attained as in conventional approaches. The second one is angle and distance approach. Matching the query premolar tooth against few other premolar teeth in the database is given in Figure 5.20 (a). It is inferred that the tooth with average Euclidean distance \( D_{\text{avg}} \) of 0.12 is coming under the Rank-1, whereas the middle and the bottom one with \( D_{\text{avg}} \) of 0.99 and 1.19 respectively are scoring Rank-6 and Rank-10 positions. Figure 5.20(b) shows the corresponding skeleton equivalent with their average distances noted aside. It is exclusive from this Figure that the tooth with Rank-1 position in contour remains the same in skeleton. For the photographic case, the top image occupies the Rank-1 position; middle and the bottom images are holding Rank-5 and Rank-8 positions respectively as given in Figures 5.20 (c) and Figure 5.20 (d). Their retrieval positions remain the same in both contour and skeleton. Then, angle and distance approach are used to measure additional parameters for contour and skeleton and is illustrated in Figure 5.21. This second method aids to make final decision about the matching. It is apparent from Figure 5.21 that the tooth with lesser \( D_{\text{avg}} \) in both contour and skeleton is scoring similar ranking also in angle and distance approach. Thus,
it makes an accurate decision about the retrieval. On the contrary, there are some cases, in which changes in ranking positions are also observed and such an output of distance measure is shown in Figure 5.22. Hence, it is also recommended to make use of texture for shape information. Normally, a tooth consists of three layers: enamel, dentine and pulp. The texture information is extracted separately from these three layers for radiographic images, which is given in Table 5.3. It shows the gray level co-occurrence matrix for three different teeth and its corresponding parameters like correlation, contrast, homogeneity and energy. It is understood from the table that out of the four parameters, correlation and homogeneity remain approximately in the same range for a single tooth for various layers.

Figure 5.20  Matching distance for radiograph and photograph using contour and skeleton (a), (b)- Radiographic contour and skeleton matching (c), (d) - Photographic contour and skeleton matching
Figure 5.21 Results of Angle and distance approach (a), (e) - Query contour (c), (g) - Query Skeleton (b), (f) - Database contour (d), (h) - Database Skeleton

Figure 5.22 A sample case for change in retrieval positions
Table 5.3 Texture Parameters

<table>
<thead>
<tr>
<th>Input tooth</th>
<th>Dentine</th>
<th>Enamel</th>
<th>Pulp</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Texture output" /></td>
<td><img src="image2" alt="Texture output" /></td>
<td><img src="image3" alt="Texture output" /></td>
<td><img src="image4" alt="Texture output" /></td>
</tr>
<tr>
<td>GLCM Parameters:</td>
<td>GLCM Parameters:</td>
<td>GLCM Parameters:</td>
<td>GLCM Parameters:</td>
</tr>
<tr>
<td>Contrast: 0.0279</td>
<td>Contrast: 1.6051</td>
<td>Contrast: 1.0655</td>
<td>Contrast: 0.8333</td>
</tr>
<tr>
<td>Correlation: 0.8102</td>
<td>Energy: 0.6916</td>
<td>Correlation: 0.8333</td>
<td>Energy: 0.6687</td>
</tr>
<tr>
<td>Energy: 0.1792</td>
<td>Homogeneity: 0.919</td>
<td>Energy: 0.6687</td>
<td>Homogeneity: 0.929</td>
</tr>
<tr>
<td>Homogeneity: 6.861</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Contrast and energy parameters are differing for enamel, dentine and pulp for a single tooth as well as for various teeth. Hence, these are the desirable parameters for matching. From this table, it is furthermore evident that the tooth in the Rank-1 position of contour and skeleton approach is also accomplishing the best match in case of texture. While comparing the first and last row of Table 5.3, it is noticeable that all these parameters are differing because the first two are premolars of maxilla and the third one is a molar of mandible and so matching may not be possible there. Wherein, a better matching performance is obtained for the first two rows. This is due to the similarity in gray levels of the three layers for premolars of two different persons. Figure 5.23 shows the gray level co-occurrence matrix for the photograph with two different lateral incisors of maxilla as a sample case. Since in photographs, it is harder to separate dentine, pulp and enamel, the texture of the whole tooth is not considered like X-ray images.
Figure 5.23 GLCM output for photographic images

Figure 5.24 GLCM output for a photographic central incisor tooth
Figure 5.25 GLCM output for another photographic central incisor

Figure 5.24 elucidates the GLCM matrix for photographic images. It is observed from this Figure that the GLCM matrix itself differs for both of these lateral incisors. The GLCM properties are also observed to be different for both. The rank of matching is calculated based on this. The GLCM for the central incisors of two different persons is shown in Figure 5.24 and Figure 5.25. Even though the GLCM seems to be quite different for both the teeth, the properties are approximately similar. Hence, this may get higher ranking in the top order retrieval. The GLCM matching for another radiographic image is shown in the Figure 5.26.
Figure 5.26 GLCM matching for Radiographs

Figure 5.27 GLCM matching for Photographs
Figure 5.27 shows a mismatching case for photograph, as the properties are differing a lot.

5.5.1 Performance Evaluation

The numbering and classification are evaluated based on accuracy and confusion matrix analysis respectively. The numbering performance metric \( \eta \) in \% is used as an evaluation measure and is given as:

\[
\eta = \frac{(m - n)}{m} \times 100 \%
\]

(5.14)

Here, \( m \) refers to the total teeth numbered and \( n \) denotes the erroneously numbered teeth. Table 5.4 depicts numbering accuracy. In this table, \( N \) denotes number of teeth and \( A \) refers to Accuracy. While comparing canine with molar and premolar, canine yields lesser accuracy of 88\%, since it resembles like premolar. In order to evaluate classification process, the confusion matrix for both radiographs and photographs is obtained and tabulated in Tables 5.5 and 5.6. In these tables, TP refers to True Positive and E refers to error in prediction.

<table>
<thead>
<tr>
<th>Table 5.4 Numbering Accuracy</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>status</th>
<th>Radiographs</th>
<th>Photographs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Molar (P)</td>
<td>Premolar (P)</td>
</tr>
<tr>
<td></td>
<td>N A(%)</td>
<td>N A(%)</td>
</tr>
<tr>
<td>Total</td>
<td>120</td>
<td>100</td>
</tr>
<tr>
<td>Accurately Numbered(m)</td>
<td>118</td>
<td>99</td>
</tr>
<tr>
<td>Erroreously Numbered(n)</td>
<td>02</td>
<td>01</td>
</tr>
</tbody>
</table>

\%
Table 5.5 Confusion matrix of Radiographs

<table>
<thead>
<tr>
<th>Known class</th>
<th>Predicted class</th>
<th>Molar(M)</th>
<th>Premolar(P)</th>
<th>Canine(C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>M</td>
<td>TPₘ = 63</td>
<td>Eₘₚ = 04</td>
<td>Eₘₖ = 04</td>
<td></td>
</tr>
<tr>
<td>P</td>
<td>EPₘ = 03</td>
<td>TPₚ = 67</td>
<td>Eₚₖ = 03</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>ECₘ = 03</td>
<td>ECₚ = 03</td>
<td>TPₖ = 67</td>
<td></td>
</tr>
</tbody>
</table>

Table 5.6 Confusion matrix for Photographs

<table>
<thead>
<tr>
<th>Known class</th>
<th>Predicted class</th>
<th>CI</th>
<th>LI</th>
</tr>
</thead>
<tbody>
<tr>
<td>CI</td>
<td>TP_CI = 63</td>
<td>EC_ILI = 04</td>
<td></td>
</tr>
<tr>
<td>LI</td>
<td>EICLI = 03</td>
<td>TP_IL = 67</td>
<td></td>
</tr>
</tbody>
</table>

Based on these, the precision and sensitivity values are observed and presented in Table 5.7. Here, precision explains the fraction of positive predictions correct and recall or sensitivity depicts fraction of positives correctly classified. In classification, the similar response is observed for the premolar and canine teeth, while molar teeth yields comparatively better precision and recall values due to its varying tooth anatomy. The central and lateral incisor classification in photographs is comparatively better than radiographs.
Table 5.7 Performance Measures

<table>
<thead>
<tr>
<th>Measure</th>
<th>Radiographs</th>
<th>Photographs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>P</td>
</tr>
<tr>
<td>Precision</td>
<td>91.3</td>
<td>90.5</td>
</tr>
<tr>
<td>(TP/ TP+ FP)</td>
<td>92.6</td>
<td>91.7</td>
</tr>
</tbody>
</table>

The matching performance is evaluated based on the Cumulative Matching Characteristic (CMC) curve and the accuracy curve. Figure 5.28 shows the CMC curve. It is plotted between top percentage of rankings and the hit rate percentage of trials.

![Cumulative Matching Characteristic Curve](image)

Figure 5.28 Cumulative Matching Characteristics Curve
It is observed from radiographic contour plot that 77.4% of images are retrieved within top-1 position. 98.3% of images are retrieved within the top-15. The same 77.4% of top-1 retrieval is achieved using skeleton also. Further, 96.7% of images are retrieved within top-15. It is slightly lower than contour approach. 69.2% of top-1 retrieval is achieved for photographic contour. A slightly lesser percentage of 66.6% is achieved as the top-1 retrieval for photographic skeleton. The top-1 retrieval of 70.9% is obtained for radiographic texture. It is comparatively higher than the photographic texture. From this, it is evident that a highest hit-rate of 0.77 is achieved for the radiographic contour and skeleton. It is also added that a least hit rate of 0.59 is achieved for the photographic texture.

The accuracy curve is plotted between top percentages of ranking with number of correct retrievals (Hofer & Marana 2007). Figures 5.29 and 5.30 elucidate the accuracy curve for all these approaches both for radiographs and photographs respectively.

![Figure 5.29 Accuracy curve for Radiographs](image-url)
The accuracy is calculated as follows:

\[
Accuracy = \frac{N_{CRR}}{N_{TCR}}
\]  

(5.15)

where, \( N_{CRR} \) denotes number of correct retrievals per ranking and \( N_{TCR} \) refers to total number of correct retrievals. From Figure 5.30, it is observed that almost a linear performance is achieved for radiographs for all the three approaches. Wherein, for photographs, a slight overlap between contour and skeleton curves is observed in Figure 5.30. The overlap is due to the change in ranking positions of contour and skeleton approaches. Since the texture differs for different illuminant conditions, the texture seems to be varying for the same tooth itself. Hence, there may be an overlap in the accuracy plot.

![Hit rate performance](image)

*Figure 5.30 Accuracy curve for Photographs*
5.5.2 Performance Evaluation with existing algorithms

The hit rate obtained in this algorithm is compared with Anil K. Jain et al (2004) and is revealed in Figure 5.31. As already discussed, the previous methods proposed by Anil K. Jain et al (2004) and Banumathi et al (2007) used only distance measure for contour matching which lead to comparatively lesser hit rate. In contrast, the proposed method not only considers the distance measure but also the angle and distance measures using texture and skeleton in addition to the contour information. Hence, this method yields higher hit rate performance and in turn improvement in accuracy of the algorithm.

![Cumulative Matching Characteristic Curve](image)

Figure 5.31 Hit-rate analysis

The algorithm is also tested against computation time with other existing techniques such as Nomir & Abdel-Mottaleb (2007) and Nomir & Abdel-Mottaleb (2008). The computation time for searching the best matched AM against PM record is 0.5 seconds in the proposed approach, which is less than 0.56 seconds as obtained by Nomir et al approach. The algorithm is also tested in terms of classification and numbering accuracy. Table 5.8 compares the classification and numbering accuracy of the proposed method for
radiographs with Lin et al (2010) approach. It is evident from this table that it achieves better accuracy with the limited dataset than that of the existing technique.

**Table 5.8 Comparative performance of Teeth numbering and classification-radiographs**

<table>
<thead>
<tr>
<th>Type of Teeth</th>
<th>Lin et al approach (2010)</th>
<th>Proposed approach</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. of teeth in the database</td>
<td>Classification accuracy (%)</td>
</tr>
<tr>
<td>Maxillary Molars</td>
<td>70</td>
<td>92.9</td>
</tr>
<tr>
<td>Mandibular Molars</td>
<td>72</td>
<td>95.8</td>
</tr>
<tr>
<td>Maxillary Premolars</td>
<td>76</td>
<td>98.7</td>
</tr>
<tr>
<td>Mandibular Premolars</td>
<td>65</td>
<td>92.3</td>
</tr>
</tbody>
</table>

5.6 SUMMARY

In this chapter, texture based victim identification is studied along with teeth classification. Classification of teeth helps to reduce the database search time. The algorithm is tested in three ways: 1) Radiographic contour and skeleton 2) photographic contour and skeleton 3) radiographic and photographic texture. The goal of this chapter is to analyze and achieve a technique with higher hit rate. The experimental results are presented for all these approaches. This proposed radiographic contour algorithm outperforms than other existing algorithms in terms of computation time and the hit-rate. It is also observed that the computation time is far reduced than fast connected
component algorithm used in chapter 2. The results of this work based on a limited data set of 62 radiographic and 42 photographic images demonstrate the efficacy of this approach for automated dental identification system. The results elaborate the importance of radiographic contour. Developing an algorithm, to extract the texture information of photographic images in order to improve the hit rate, is an open issue and it is the outcome of this research.