

Human Identification using Dental Radiograph



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Under the Supervision of

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Declaration

We hereby declare that this thesis has been done based on the results we obtained from our work. Due acknowledgement has been made on text. This thesis neither in parts nor as a whole have been submitted previously by anyone of any institute or university for the award of any degree.

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Abstract

Dental biometrics is a very important feature in human identification. It can help greatly in Forensic Dentistry. In this paper, we present a method for identifying people based on shapes and appearances of their teeth using Edge detection, pixel value counting and feature extraction. This method automatically detects important features to identify a person. Wiener filter is used to reduce noise and provide a smooth image. For edge detection, we have used Canny Edge Detection algorithm where preprocessed filtered grey scale image's edge has been defined through Gaussian filtering and Edge thresholding. From the given edge detected image canny method determines the region of shape which represents binary pixel value. This pixel value can be used in image identification. Furthermore, the SURF algorithm used to define interest points. Given a query image (i.e., Postmortem radiograph), each tooth is matched with the archived teeth in the database (Antemortem radiographs). Our goal of using appearance and shape-based features together is to overcome the drawback of using only the contour of the tooth, which can be strongly affected by the quality of the images. The experimental results are based on a database of 20 panoramic x ray images show that our method is effective in identifying individuals based on their dental radiographs.

Keywords: Edge detection, pixel value, SURF algorithm, feature extraction, query, dental radiograph, recognize, identification, matching, interest points.

CHAPTER 01

Introduction

The dental feature is one of the most important biometric information along with fingerprint, facial recognition, hand geometry, or iris identification. It can be used to identify a person with postmortem biometric because teeth anatomy and tooth structure still remain similar to when the person died more than a couple of weeks or died for a long time. It also can be used to identify a person, if someone does plastic surgery on the face. A set of teeth images have been used as the template and saved in the image database. The identification is carried out by comparing postmortem (PM) images with antemortem (AM) records of missing people to find the best match [1]. In current security conditions, biometric identification is the most promising way to authenticate humans with the highest accuracy rate. From various modalities, dental biometrics has a leading edge over others. We use the dental radiographic image of teeth of different persons. The radiographic image is converted to the gray-scale image. Reduce noise of image and convert to smooth image by using Wiener filtering. Edge detect by using canny edge detector and SURF method for feature detection, extraction and matching. The main process of this system contains image segmentation, pixel value calculation, feature detection, extraction and matching.

1.1 Motivation

Dental features have always played a very important role in forensics. This is very important for any country in the world. Every day many accidents occur and some accident is so critical that the face of the victim cannot be identified. In that case, it is hard to detect victim's details without fixing his/her face also, sometimes the face cannot be reconstructed. By using our system one can easily identify the victim. On the other hand, many wanted criminals conduct surgery on their faces to change their identity. We can also identify them by using our human identification system and show their true identity from the datasets in our database. V. Pushparaj, U. Gurunathan and B. Arumugam used shape extraction and shape matching for human identification[2]. Frontal view human face detection and recognition by L. S. Balasuriya and Dr. N. D. Kodikara, use template matching strategy [3] in their system. Human Identification from Dental X-Ray Images by Omaira Nomir and Mohamed Abdel-Mottaleb, based on the shape and appearance of the teeth

and also use segmentation of grey scale images [4]. We are using their combined way with our own method for identification process.

1.2 Contribution Summary

The main purpose of this project is, this project will enable forensic doctors to identify victims in case mass disaster. We used some existing methods like Canny Edge Detection, Weiner Filtering and SURF Feature Extraction method and combined them into a single workspace. Wiener filter processing determines the region of smoothed shape by reducing noise[5]. For edge detection technique we have used canny edge detection algorithm where filtered grayscale image's edge has been defined through Gaussian filtering and Edge thresholding. The binary property of canny edged image allows calculating pixel value easily. For feature extraction SURF Method is used, which is able to find the unique points of an image. Furthermore, the SURF algorithm used to scale the unique points[6]. Lastly, match the extracted information of those points with another image from database and get result.

1.3 Thesis Outline

- Chapter 2 provides the Background study in details including the algorithms and techniques used in the system
- Chapter 3 describes the proposed model along with implementation details
- Chapter 4 presents the results of the experiment along with performance analysis and comparisons
- Chapter 5 concludes the paper specifying the limitations and challenges while planning future development of the project

CHAPTER 02

Background Analysis

2.1 Previous Works and Technical Overview

The objective of the research reported is to automate the process of forensic dentistry. In forensic dentistry, the postmortem dental record is compared against antemortem records pertaining to some presumed identity. According to Hong Chen's[7] report, a semi-automatic process will be able to compare the PM dental records against AM dental records and find the multiple identities in order to determine the closest match. The dental records are usually available as radiographs. Usually noise present in radiograph images. For reducing the noise of images they take some steps. The first step is radiograph segmentation where the goal is to segment the radiograph into blocks such that each block has a tooth in it. Then they tried to detect gap valley of jaw's image. Since the teeth usually have a higher gray level intensity than the jaws and other tissues in the radiographs due to their higher tissue density, the gap between the upper and lower teeth will form a valley in the histogram. And they detect the gap valley of jaw's image. The second process is tooth isolation. The method to isolate each tooth from its neighbours is similar to the method to separate the lower and upper jaws. Due to the poor quality of some images, they found segmentation errors. The errors are categorized into over segmentation and under-segmentation. The user can delete the segmentation lines of over-segmentation and add lines for under-segmentation and generalize the crown centre. Next, they use contour extraction. Where they identified crown, followed by the root contour extraction. They used crown shape extraction to the identified crown center of teeth and capture the crown portion. They also used root shape extraction where it helps to compute the root of teeth from the dental image. Finally, they matching the shape of PM image from AM image. They measure the root distance and crown of the teeth in shape matching process. According to Hong Chen's report, they achieved 45%-50% accuracy in skull recognition process. But in our project, we tried to overcome the barriers and lac-kings of Hong Chen project and tried to achieve the maximum accuracy percentages.

On the other hand, according to Omaina Nomir's[8] report, they also used jaws of a human for the recognition process. They used several steps for computing this. The first step is radiograph segmentation and teeth separation where segmentation separates the teeth from the background using a two-step thresholding technique. The second stage separates the upper jaw from the lower jaw and then separates each tooth using integral projection. Next, they used iterative thresholding. Iterative thresholding was used to automatically segment CT lung images in order to accommodate the small variations that are expected across a population of subjects. By using Iterative thresholding they detect all the edges of teeth. Then in teeth separating process they separate each tooth of upper and the lower jaws. After that, they can easily separate upper and lower jaws from the dental image. Finally, they matched the PM image with AM image. In the end of their project, they achieved 70% accuracy. Our main focus is to achieve above 80% accuracy in our project. Nomir's project is our ideal project that we want to follow and try to overcome the limitation. In our skull recognition research, we read several research papers but selected these two research for our future progress. We tried to follow these two research and hopefully minimized all the limitations and gain maximum accuracy. However, Vijayakumari Pushparaj[2] method proposed a connected component algorithm for shape extraction, similarity and distance measures for matching purpose.

2.2 Biometric Identification

Biometric identification is a very famous and promising technique by which a person can be uniquely identified by evaluating one or more distinguishing biological traits[9]. Unique identifiers include fingerprints, hand geometry, earlobe geometry, retina and iris patterns, voice waves, DNA, and signatures. Though there are several methodologies to make any of those identifiers work for identification, the process and results are same. For any process to work, what we need is a record of a person's unique characteristic captured and kept in a database. Later on, when identification is required, a new record is captured and compared with the previous record in the database. If the data in the new record matches that in the database record, the person's identity is confirmed. When none of those identifiers is properly available, there is another system to identify a person which is the dental biometric system.

2.2.1 Dental Biometric System

Dental biometrics deals with human identification from dental characteristics. It uses information about dental structures to automatically identify people from human remains. The methodology is mainly applied to the identification of victims of massive disasters. The process of dental identification consists of measuring dental features, labelling individual teeth with tooth indices, segmentation, matching of dental features etc. Dental radiographs are the major source for obtaining dental features[10]. Commonly used dental features are based on tooth morphology (dental shape) and appearance which are core points of our proposed model.

2.2.2 Dental Radiograph

A dental radiograph is a photographic image produced on film by the passage of X-rays through teeth and supporting structures. Dental radiographs are essential for oral diagnostic procedures. There are three types of dental radiographs.

2.2.2.1 Bitewings X-ray

Bitewing x-ray shows details of the upper and lower teeth in one area of the mouth. Each bite-wing shows a tooth from its crown (the exposed surface) to the level of the supporting bone. Figure 2.1 shows an example of Bitewing X-ray image.

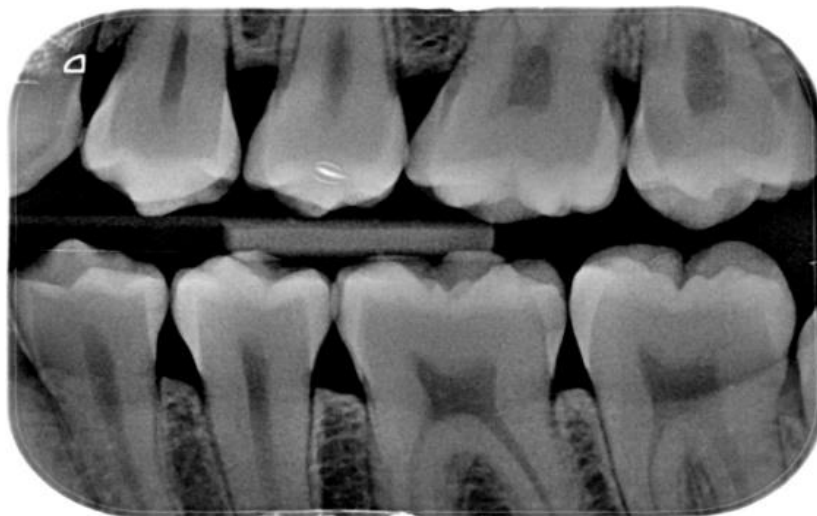


Figure 2.1: Bitewing X- ray

2.2.2.2 Periapical X-rays

It shows the whole tooth — from the crown, to beyond the root where the tooth attaches into the jaw. Each periapical x-ray shows all teeth in one portion of either the upper or lower jaw. Figure 2.2 depicts the periapical X-ray radiograph.

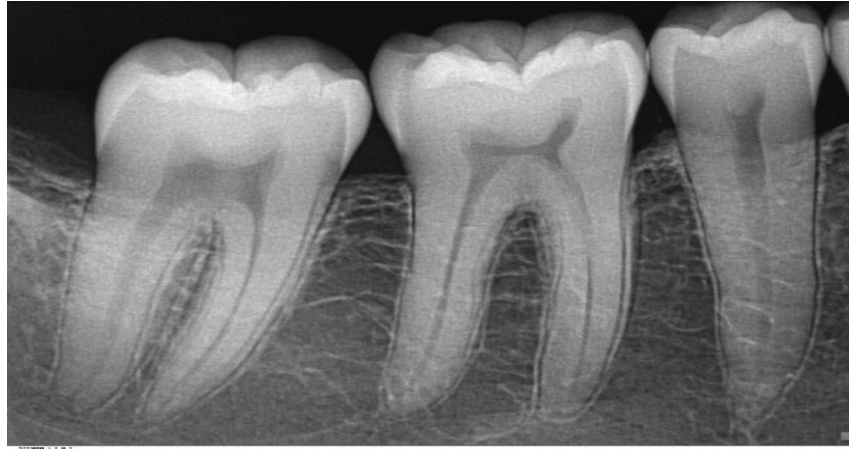


Figure 2.2: Periapical X-ray

2.2.2.3 Panoramic X-ray

It gives a broader overview of entire dentition. It shows not only teeth also sinus, upper and lower jaws. Figure 2.3 is an illustration of a panoramic X-ray image.



Figure 2.3: Panoramic X-ray

2.3 Segmentation

Segmentation partitions an image into distinct regions containing each pixel with similar attributes. To be meaningful and useful for image analysis and interpretation, the regions should strongly relate to depicted objects or features of interest. Meaningful segmentation is the first step from low-level image processing transforming a greyscale or color image into one or more other images to high-level image description in terms of features, objects, and scenes [11]. The success of image analysis depends on the reliability of segmentation, but an accurate partitioning of an image is generally a very challenging problem.

2.3.1 Radiograph Segmentation

The goal of radiograph segmentation is to localize the region of each tooth in a dental X-ray image. They may suffer from poor quality, low contrast and uneven exposure that complicate the task of segmentation which can be solved by some image processing techniques.

2.3.2 Image Pixel

A pixel is the smallest unit of a digital image or graphic that can be displayed on a digital display device. Pixels are also known as picture elements which are combined to form a complete image, video, text or any visible thing on any kind of digital display. A pixel is represented by a dot or square on a computer monitor display screen. Pixels are the basic building blocks of a digital image or display and are created using geometric coordinates. Depending on the graphics card and display monitor, the quantity, size and color combination of pixels varies and is measured in terms of the display resolution. Which means images that are displayed on a digital screen like a monitor are simply in a digital form that is made up of thousands of tiny dots each of a single color. These dots are called pixels in the matter of digital image display.

Digital images are made up of these dots of solid color. They fit together side by side with no spaces in between. These vary according to the device they are displayed on. Although not usually visible to the eye, an image is made up of many tiny pixels, each of a single color that is so small that our eyes see them as continuous tone. Normally we view images as continuous tones, unaware of the structure underneath. But when an image is digitized it is broken up into tiny blocks with a description of the color value at each point.

A monitor represents each pixel as three strips and varies the intensity of each strip to render what looks like a particular color. This means when an image is viewed on a screen like a computer, a television, or projection onto a wall, the screen itself is made up of pixels. These are not solid colors but are each made up of three strips of three prime colors which are Red, Green and Blue (RGB). The image being viewed is still made of solid blocks of colored pixels, but you are viewing them as tiny colored stripes. The screen varies the intensity of these stripes to give the impression that they are each one solid color when viewed at the normal viewing distance.

2.3.3 Grayscale Image

A grayscale image is an image where the only colors are shades of gray. The benefit of the grayscale image is that less information needs to be provided for each pixel. For this color, components of red, blue and green color have equal intensity. Therefore, providing a single intensity value for each pixel does the work. The representation of the gray image is basically the combination of black and white color shades. Figure 2.4 shows a grayscale image of a panoramic X-ray.

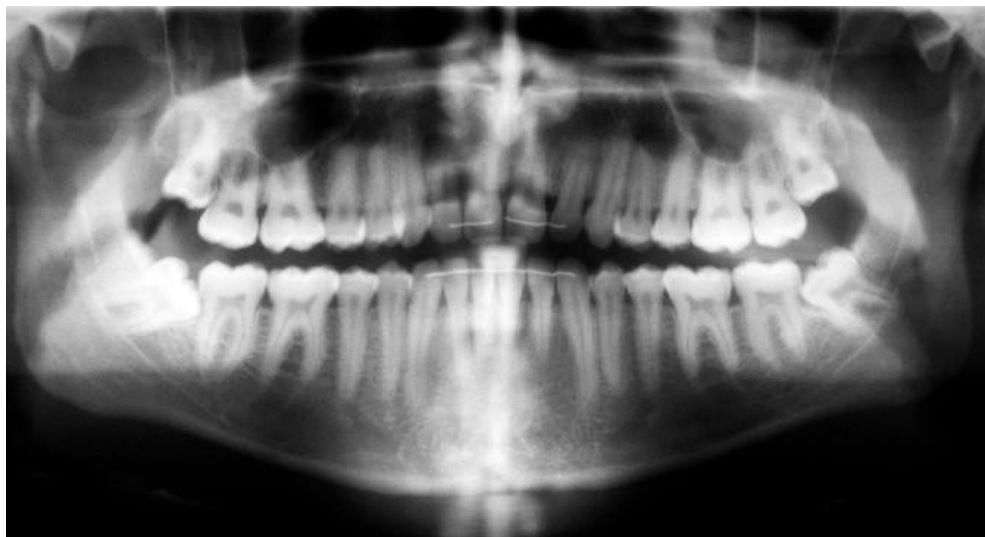


Figure 2.4: Grayscale Image

2.3.4 Wiener Filtering

The Wiener filtering is optimal in terms of the mean square error. It minimizes the overall mean square error in the process of inverse filtering and noise smoothing. The Wiener filtering is a linear estimation of the original image. The approach is based on a stochastic framework. The orthogonality principle implies that the Wiener filter in Fourier domain can be expressed by equation (1).

$$W(f_1, f_2) = \frac{H^*(f_1, f_2)S_{xx}(f_1, f_2)}{|H(f_1, f_2)|^2 S_{xx}(f_1, f_2) + S_{\eta\eta}(f_1, f_2)}, \quad (1)$$

Here, $S_{xx}(f_1, f_2)$, $S_{\eta\eta}(f_1, f_2)$ are respectively power spectra of the original image and the additive noise, and $H(f_1, f_2)$ is the blurring filter. It is easy to see that the Wiener filter has two separate part, an inverse filtering part and a noise smoothing part. It not only performs the deconvolution by inverse filtering (highpass filtering) but also removes the noise with a compression operation (lowpass filtering).

To implement the Wiener filter in practice we have to estimate the power spectra of the original image and the additive noise. For white additive noise, the power spectrum is equal to the variance of the noise. To estimate the power spectrum of the original image many methods can be used. A direct estimate is the periodogram estimate of the power spectrum computed from the observation of equation (2).

$$S_{yy}^{per} = \frac{1}{N^2} [Y(k, l)Y(k, l)^*] \quad (2)$$

Here, $Y(k, l)$ is the DFT of the observation. The advantage of the estimate is that it can be implemented very easily without worrying about the singularity of the inverse filtering. Another estimate which leads to a cascade implementation of the inverse filtering and the noise smoothing is given in equation (3).

$$S_{xx} = \frac{S_{yy} - S_{\eta\eta}}{|H|^2}, \quad (3)$$

It is a straightforward result of the fact: $S_{yy} = S_{\eta\eta} + S_{xx}|H|^2$. The power spectrum S_{yy} can be estimated directly from the observation using the periodogram estimate. This estimate results in a cascade implementation of inverse filtering and noise smoothing which can be defined by equation (4).

$$W = \frac{1}{H} \frac{S_{yy}^{per} - S_{\eta\eta}}{S_{yy}^{per}}. \quad (4)$$

To illustrate the Wiener filtering in image restoration we have used the grayscale form of a panoramic x-ray. Then the Wiener filtering is applied to the image with a cascade implementation of the noise smoothing and inverse filtering. Figure 2.5(a) represents a grayscale image and 2.5(b) is the same image with Wiener filter applied on it.



Figure 2.5(a): grayscale image

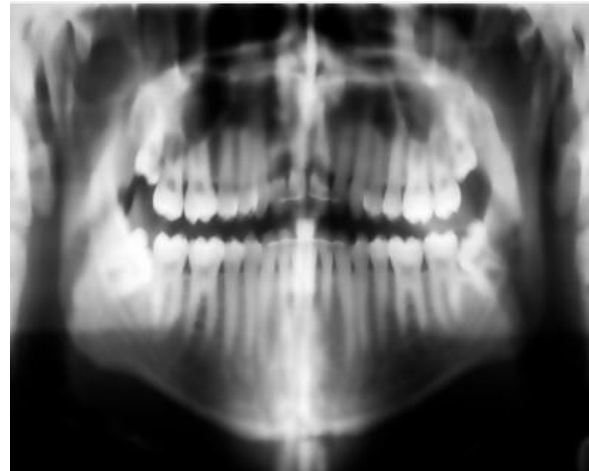


Figure 2.5(b): Image after Wiener filtering

2.3.5 Binary Image

Binary image which is also called as black and white image is a digital image that has only two possible values black and white for each pixel. So, there are only two intensities which are full intensity '1' and no intensity '0'. Full intensity gives white color and no intensity gives black color and unlike gray image, there are no shades between. While a grayscale image has a continuous range of gray values, a binary image has only two possible values for each pixel. The number of

white and black color dots can be measured which can be used for image matching or comparing between two images.

2.4 Edge Detection

Edge detection is one of the most commonly used operations in image analysis, and there are more algorithms in the literature for enhancing and detecting edges. The edge representation of an image significantly reduces the quantity of data to be processed, yet it retains essential information regarding the shapes of objects in the scene. This explanation of an image is easy to incorporate into a large amount of object recognition algorithms used in computer vision along with other image processing applications. The major property of the edge detection technique is its ability to extract the exact edge line with good orientation as well as more literature about edge detection has been available in the past three decades. On the other hand, there is not yet any common performance directory to judge the performance of the edge detection techniques [12]. The performance of an edge detection techniques are always judged personally and separately dependent to its application. Edge detection is a fundamental tool for image segmentation. Edge detection methods transform original images into edge images benefits from the changes of grey tones in the image. In image processing especially in computer vision, the edge detection treats the localization of important variations of a gray level image and the detection of the physical and geometrical properties of objects of the scene [13]. It is a fundamental process detects and outlines of an object and boundaries among objects and the background in the image. Edge detection is the most familiar approach for detecting significant discontinuities in intensity values. Edges are local changes in the image intensity. Edges typically occur on the boundary between two regions. The main features can be extracted from the edges of an image. Edge detection has major feature for image analysis [14]. These features are used by advanced computer vision algorithms. Edge detection is used for object detection which serves various applications like medical image processing, biometrics etc. Edge detection is an active area of research as it facilitates higher level image analysis. There are three different types of discontinuities in the grey level like point, line and edges. Spatial masks can be used to detect all the three types of discontinuities in an image. There are many edge detection techniques in the literature for image segmentation. The most commonly used discontinuity based edge detection techniques are Roberts edge detection, Sobel

Edge Detection, Prewitt edge detection, Canny Edge Detection etc. Figure 2.6 is an example of edge detection procedure called Canny Edge Detection.

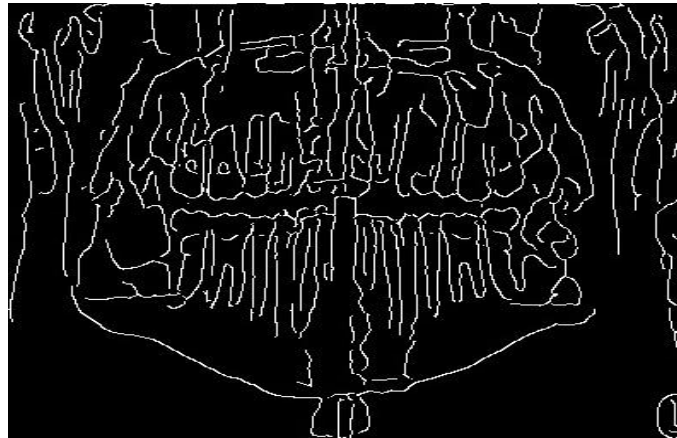


Figure 2.6: Canny Edge Detection

2.4.1 Canny Edge Detection

The Canny edge detection technique is one of the standard edge detection techniques. It was first created by John Canny for his Master's thesis at MIT in 1983, and still outperforms many of the newer algorithms that have been developed. To find edges by separating noise from the image before find edges of image the Canny is a very important method. Canny method is a better method without disturbing the features of the edges in the image afterwards it applying the tendency to find the edges and the serious value for threshold. The algorithmic steps are as follows:

- Convolve image $f(r, c)$ with a Gaussian function to get smooth image $f^{\wedge}(r, c)$. $f^{\wedge}(r, c) = f(r, c) * G(r, c, 6)$
- Apply first difference gradient operator to compute edge strength then edge magnitude and direction are obtain as before.
- Apply non-maximal or critical suppression to the gradient magnitude.
- Apply threshold to the non-maximal suppression image.

Unlike Roberts and Sobel, the Canny operation is not very susceptible to noise.

2.5 Speeded up robust features (SURF)

Speeded up robust features (SURF) is a local feature detector and descriptor. The task of finding correspondences between two images of the same scene or identify object is part of many computer vision application such as object recognition, image registration, classification or 3D reconstruction etc. where it can be used. It is partly inspired by the scale-invariant feature transform (SIFT) descriptor which is another most appealing descriptor for practical uses. The standard version of SURF is several times faster than SIFT.

In terms of searching for discrete image correspondences – the goal of this work – can be divided into three main steps. First, ‘interest points’ are selected at distinctive locations in the image, such as corners, blobs, and T-junctions. The most valuable property of an interest point detector is its repeatability, i.e. whether it reliably finds the same interest points under different viewing conditions. Next, the neighborhood of every interest point is represented by a feature vector. This descriptor has to be distinctive and, at the same time, robust to noise, detection errors, and geometric and photometric deformations. Finally, the descriptor vectors are matched between different images. The matching is often based on a distance between the vectors, e.g. the Mahalanobis or Euclidean distance. The dimension of the descriptor has a direct impact on the time this takes, and a lower number of dimensions is therefore desirable.

2.5.1 Feature Detection

In the first step of detecting interest points in an image, the detector works based on the Hessian matrix but uses a very basic approximation, just as DoG is a very basic Laplacian-based detector. It relies on integral images to reduce the computation time and we therefore call it the ‘Fast-Hessian’ detector.

Fast-Hessian Detector: The determinant of the Hessian matrix is used as a measure of local change around the point and points are chosen where this determinant is maximal. In contrast to the Hessian-Laplacian detector by Mikolajczyk and Schmid, SURF also uses the determinant of the Hessian for selecting the scale, as is also done by Lindeberg. Given a point $p=(x, y)$ in an image I , the Hessian matrix $H(p, \sigma)$ at point p and scale σ , is given by equation (3)

$$\mathcal{H}(\mathbf{x}, \sigma) = \begin{bmatrix} L_{xx}(\mathbf{x}, \sigma) & L_{xy}(\mathbf{x}, \sigma) \\ L_{xy}(\mathbf{x}, \sigma) & L_{yy}(\mathbf{x}, \sigma) \end{bmatrix} \quad (5)$$

Where $L_{xx}(x, \sigma)$ is the convolution of the Gaussian second order derivative of gaussian with the image $I(x,y)$ in point x , and similarly for $L_{xy}(x, \sigma)$ and $L_{yy}(x, \sigma)$. The 9×9 box filters are approximations for Gaussian second order derivatives with $\sigma = 1.2$ and represent the lowest scale (i.e. highest spatial resolution).

Interest points can be found at different scales, partly because the search for correspondences often requires comparison images where they are seen at different scales. In other feature detection algorithms, the scale space is usually realized as an image pyramid. Images are repeatedly smoothed with a Gaussian filter. Then they are subsampled to get the next higher level of the pyramid. Therefore, several floors or stairs with various measures of the masks are calculated from the equation (6).

$$\sigma_{\text{approx}} = \text{current filter size} \times \left(\frac{\text{base filter scale}}{\text{base filter size}} \right) \quad (6)$$

The scale space is divided into a number of octaves, where an octave refers to a series of response maps of covering a doubling of scale. In SURF, the lowest level of the scale space is obtained from the output of the 9×9 filters.

Hence, unlike previous methods, scale spaces in SURF are implemented by applying box filters of different sizes. Accordingly, the scale space is analyzed by up-scaling the filter size rather than iteratively reducing the image size. The output of the above 9×9 filter is considered as the initial scale layer at scale $s = 1.2$ (corresponding to Gaussian derivatives with $\sigma = 1.2$). The following layers are obtained by filtering the image with gradually bigger masks, taking into account the discrete nature of integral images and the specific filter structure. This results in filters of size 9×9 , 15×15 , 21×21 , 27×27 , Non-maximum suppression in a $3 \times 3 \times 3$ neighborhood is applied to localize interest points in the image and over scales. The maxima of the determinant of the Hessian matrix are then interpolated in scale and image space with the method proposed by Brown, et al. Scale space interpolation is especially important in this case, as the difference in scale between the first layers of every octave is relatively large.

2.5.2 Feature Extraction/Description

The good performance of SIFT compared to other descriptors is remarkable. It is mixing of crudely localized information and the distribution of gradient related features seems to yield good distinctive power while fending off the effects of localization errors in terms of scale or space. Using relative strengths and orientations of gradients reduces the effect of photometric changes. The SURF descriptor is based on similar properties, with a complexity stripped down even further. The first step consists of fixing a reproducible orientation based on information from a circular region around the interest point. Then, construct a square region aligned to the selected orientation, and extract the SURF descriptor from it.

Orientation assignment

In order to achieve rotational invariance, the orientation of the point of interest needs to be found. The Haar wavelet responses in both x- and y-directions within a circular neighborhood of radius $6s$ around the point of interest are computed, where s is the scale at which the point of interest was detected. The obtained responses are weighted by a Gaussian function centered at the point of interest, then plotted as points in a two-dimensional space, with the horizontal response in the abscissa and the vertical response in the ordinate. The dominant orientation is estimated by calculating the sum of all responses within a sliding orientation window of size $\pi/3$. The horizontal and vertical responses within the window are summed. The two summed responses then yield a local orientation vector. The longest such vector overall defines the orientation of the point of interest. The size of the sliding window is a parameter that has to be chosen carefully to achieve a desired balance between robustness and angular resolution.

Descriptor Components

To describe the region around the point, a square region is extracted, centered on the interest point and oriented along the orientation as selected above. The size of this window is $20s$. The interest region is split into smaller 4×4 square sub-regions, and for each one, the Haar wavelet responses are extracted at 5×5 regularly spaced sample points. The responses are weighted with a Gaussian to offer more robustness for deformations, noise and translation.

2.5.3 Matching

By comparing the descriptors obtained from different images, matching pairs can be found.

CHAPTER 03

Proposed Model

3.1 System Design

Figure 3.1 shows a block diagram of our proposed model. It demonstrates our algorithm set up. At first, we took a radiograph of a person and converted the RGB image into Gray image. Then we resized the image in a specific ratio. After that, we have filtered the image with Wiener filtering which smoothens the image by removing noise and use it for further processing. Then we applied canny edge detection algorithm for edge detection where the binarized property of the output image is used to calculate the pixel values which we have used as our first evaluation technique for image comparing. After that, we have applied another process for comparing which is SURF algorithm for feature detection, extraction and matching. By approaching two different evaluation processes, we tried to provide more accuracy in result in term of identification.

3.2 Methodology

3.2.1 Data collection

For collecting data, we took the help of the doctor of a local clinic to collect the panoramic X-ray images. Then we took photos of those X-ray films with a camera. As a result, all of the images we collected were in RGB.

3.2.2 Tools used

We used MATLAB R2016a Simulation tools for data analysis. We used core-i3, 6th gen, Ram-4GB, window 10 64bit PC. We use 20 images for each matching process.

Work Flow for our proposed model

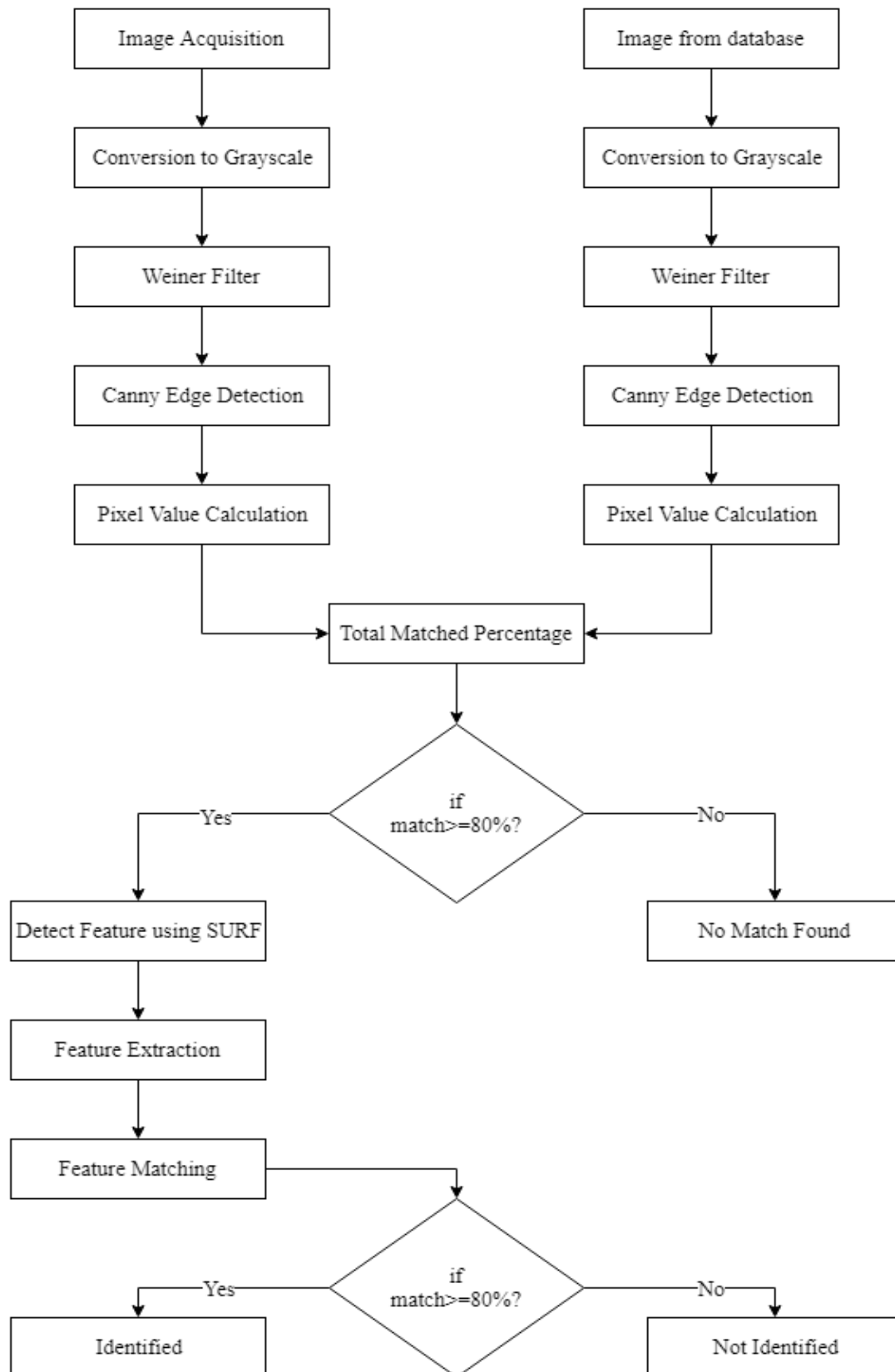


Figure 3.1: Block diagram of the proposed model

3.2.3 Segmenting Grayscale Image

We are basically using average method for RGB to grey scale conversion. The reason for converting the RGB image to grey scale image is that in many applications of image processing, colour information doesn't help us identify important edges or other features. Grayscale simply reduces complexity as it transforms from a 3D pixel value (R, G, B) to a 1D value. Many image processing applications do not work well with 3D pixels. For example, edge detection. There are many reasons for not working perfectly like if one of the colour channels holds more vital information than the others, it can overweight this channel. We took the image for identification and another from our dataset for comparing and converted both into grey scale image. In figure 3.2(a) we can see the first image and in figure 3.2(b) the second image converted to Grayscale.

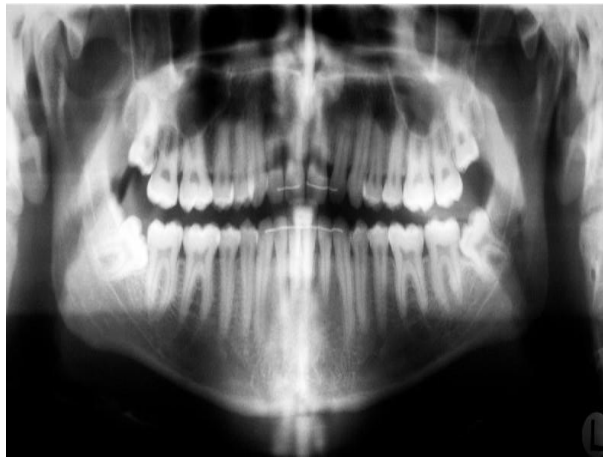


Figure 3.2(a) : Grayscale image 1



Figure 3.2(b) : Grayscale image 2

3.2.4 Wiener Filtering

Weiner filter is a filter that makes the image smooth and removes noise from the image. In order to get good result for edge detection process, we needed smooth and de-noised image. So we applied Wiener filtering in both of the images for further processing. Figure 3.3(a) and 3.3(b) are the corresponding Wiener filtered images which were converted into grayscale in the precious section.



Figure 3.3(a) : Wiener image 1



Figure 3.3(b): Wiener image 2

3.2.5 Canny Edge Detection

In order to proceed to our next step, we need to determine the presence of edges in our experimental Wiener filtered images which we have converted from grayscale images and outline them in a proper way[15]. It will allow us to simplify and minimize the amount of image data for further procedure. In our project, we are using canny edge detection method. Canny edge detector works by following steps –

Smoothing: Smooth the image with a two dimensional Gaussian, one in the x-direction and the other in the y-direction. As the result of edge detection get affected by image noise, the image needs filtering. By using Gaussian filtering, we can reduce the effects of obvious noise on the edge detector. Figure 3.4 shows Gaussian filter used to create the adjacent image, with $\sigma = 1.4$. The equation for a Gaussian filter kernel of size $(2k+1) \times (2k+1)$ is given by equation (7). An example of the Gaussian filter is also given in figure 3.4.

$$H_{ij} = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{(i-(k+1))^2 + (j-(k+1))^2}{2\sigma^2}\right); 1 \leq i, j \leq (2k+1) \quad (7)$$

$$B = \frac{1}{159} \begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix} * A.$$

Figure 3.4: Example of a 5×5 Gaussian filter

Finding gradients: The edges should be marked where the gradients of the image have large magnitudes. The edge gradient and direction can be found by the formula given in equation (8) & (9).

$$G = \sqrt{G_x^2 + G_y^2} \quad (8)$$

$$Angle(\theta) = \tan^{-1} \left(\frac{G_y}{G_x} \right) \quad (9)$$

Here, G is the edge gradient and θ represents the direction.

Non-maximal Suppression: Edges will occur at points where the gradient is at a maximum. Hence, all points at a maximum should not be suppressed. To facilitate this, the magnitude and direction of the gradient are computed at each pixel. After that for each pixel check if the magnitude of the gradient is greater at one pixel's distance away in either the positive or the negative direction perpendicular to the gradient. If the pixel is not larger than both, suppress it.

Edge Thresholding: The method of thresholding used by the Canny Edge Detector is referred to as "hysteresis". It utilizes both a high threshold and a low threshold. If a pixel has a value above the high threshold, it is set as an edge pixel. If a pixel has a value above the low threshold and is the neighbour of an edge pixel, it is set as an edge pixel as well. But if a pixel has a value above the low threshold but is not the neighbour of an edge pixel, it is not set as an edge pixel. If a pixel has a value below the low threshold, it is never set as an edge pixel. An example is shown in Figure 10.

Finally, after following all of those above steps, strong edge points should be determined by suppressing all edges that are not connected to a very strong edge. Thus our edge determination process is complete [16]. Figure 3.5(a) & 3.5(b) are the output images of previously filtered image 1 & 2 respectively.

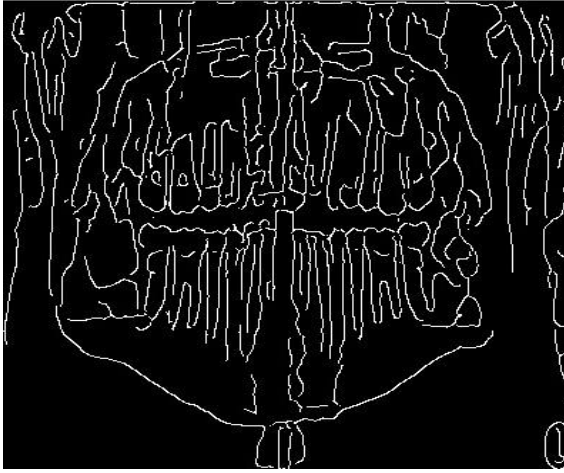


Figure 3.5(a): Image 1 after edge detection Figure 3.5(b): Image 2 after edge detection

3.2.6 Pixel value calculation

Canny edged image has a property of presenting an image in black and white. Therefore there are black points which represent 0s and white points which represent 1s. These pixel values can be measured. So, we have calculated the number of white points which represent the edges of both images.

3.2.7 Total match percentage

After counting the number of white points of both images, we have compared both images by calculating the percentage of matched points. From equation (10) we can find out the difference between the two images that are being compared. Here, W_1 represents the number of white points found in image 1 and W_2 represents number of white points found in image 2. From equation (11) we can calculate the similarity between the images.

$$Difference = \left| \frac{W_1 - W_2}{\frac{W_1 + W_2}{2}} \right| * 100 \quad (10)$$

$$Similarity = (100 - Difference)\% \quad (11)$$

If the result is less than 80% then we declared as 'Not identified'. If the result is equal or more than 80% then we went through another evaluation process where we used SURF algorithm to get efficient result. The reason behind second evaluation is that if both person's jaw structures are nearly similar then the number of white points don't vary that much. In that case, it may provide false result. That is why we have applied another algorithm to ensure efficient and reliable result.

3.2.8 Feature detection

For this process we again took the gray scale version of both images and applied SURF feature detection algorithm which detects points of interest which contains SURF features and also marks those points in the image.

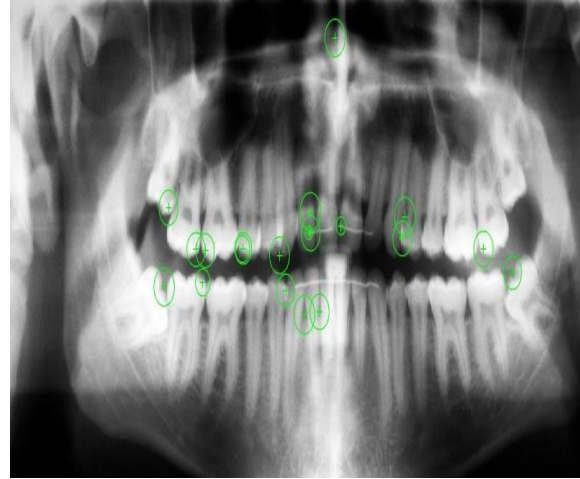
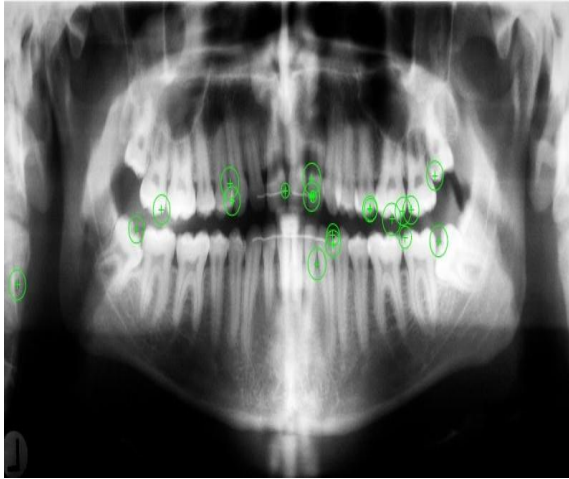


Figure 3.6(a): Detecting points in Image 1 Figure 3.6(b): Detecting points in Image 2

3.2.9 Feature Extraction

After detecting interest points, we applied feature extraction algorithm which returns extracted feature vectors and their corresponding locations from image.

The function derives the descriptors from pixels surrounding an interest point. The pixels represent and match features specified by a single-point location. Each single-point specifies the center location of a neighborhood.

3.2.10 Matching points

Finally we applied Matching algorithm within the extracted feature information of both images which returns indices of the matching features in the two input feature sets. From the equation (12) we can calculate the percentage of matches found in the two images.

$$\text{Matching percentage} = \frac{\text{Number of matching points}}{\text{Minimum number of interest points}} * 100 \quad (12)$$

In figure 3.7 we can see the final output image after using SURF method on the two images that were matched with each other.

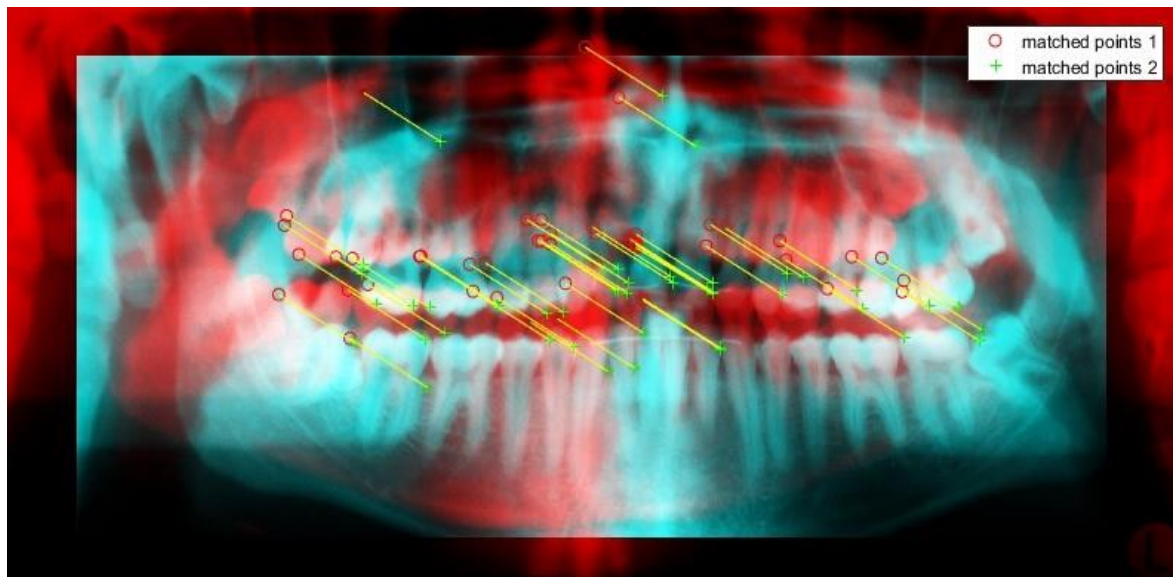


Figure 3.7 : Final matching points

CHAPTER 04

Experimental Analysis

In this section, the performance of the proposed human identification is evaluated. The proposed method is tested on Panoramic X-ray image dataset. Using 2.5GHz Intel core i3 processor the experiments were performed.

We have already demonstrated the set up for our proposed model in work flow and also described our implementation steps. Now we will present the result of our experimentation. Table 4.1 represents the amount of match found between two test images and the images in our dataset where same images are deliberately added after some minor editing to check the potency of our method.

Serial No.	Image for identification	Image from dataset	Total matched (%)
1	Image 1	Image 3	85.69
2	Image 1	Image 4	93.74
3	Image 1	Image 5	85.41
4	Image 1	Image 6	100
5	Image 1	Image 7	94.41
6	Image 1	Image 8	93.95
7	Image 1	Image 9	51.67
8	Image 1	Image 10	97.79
9	Image 1	Image 11	95.94
10	Image 1	Image 12	95.40
11	Image 2	Image 3	100
12	Image 2	Image 4	79.48
13	Image 2	Image 5	71.25
14	Image 2	Image 6	85.69
15	Image 2	Image 7	80.14
16	Image 2	Image 8	91.72
17	Image 2	Image 9	38.43
18	Image 2	Image 10	87.89
19	Image 2	Image 11	89.74
20	Image 2	Image 12	90.27

Table 4.1: Result analysis by pixel value calculation

Serial No.	Image for identification	Image from dataset	Total matched (%)
1	Image 1	Image 3	1.7
2	Image 1	Image 4	5.1
3	Image 1	Image 5	<u>100</u>
4	Image 1	Image 6	<u>100</u>
5	Image 1	Image 7	3.45
6	Image 1	Image 8	1.72
7	Image 1	Image 10	0
8	Image 1	Image 11	5.17
9	Image 1	Image 12	1.7
10	Image 2	Image 3	<u>100</u>
11	Image 2	Image 6	1.7
12	Image 2	Image 7	6.01
13	Image 2	Image 8	4.37
14	Image 2	Image 10	2.17
15	Image 2	Image 11	5.19
16	Image 2	Image 12	<u>97</u>

Table 4.2: Result analysis by SURF algorithm

Figure 4.1 shows the matched percentages for Image 1 where (a) shows the amount of match found after pixel calculation and (b) shows the percentage of match found after applying SURF feature extraction. Also, figure 4.1(b) only shows results for the images which have more than 80% match in figure 4.1(a).

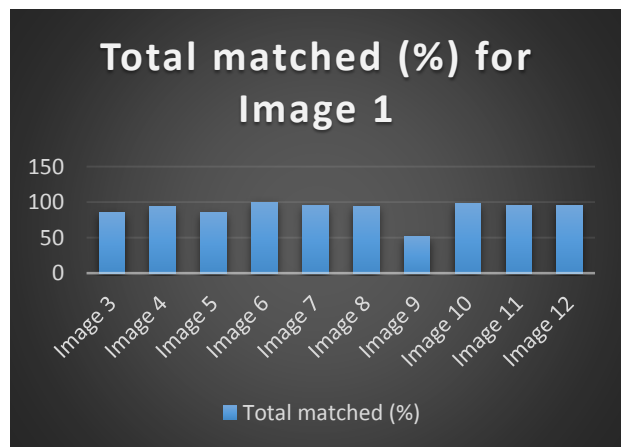


Figure 4.1(a): Matched (%) after pixel count

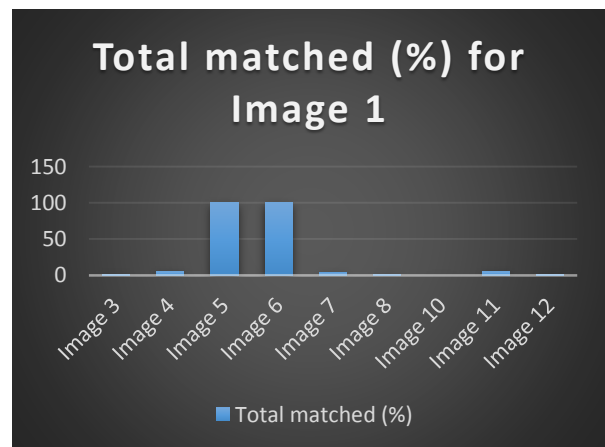


Figure 4.2(b): Matched (%) after SURF

Figure 4.2 shows the matched percentages for Image 2 where (a) shows the amount of match found after pixel calculation and (b) shows the percentage of match found after applying SURF feature extraction. Also, figure 4.2(b) only shows results for the images which have more than 80% match in figure 4.2(a).

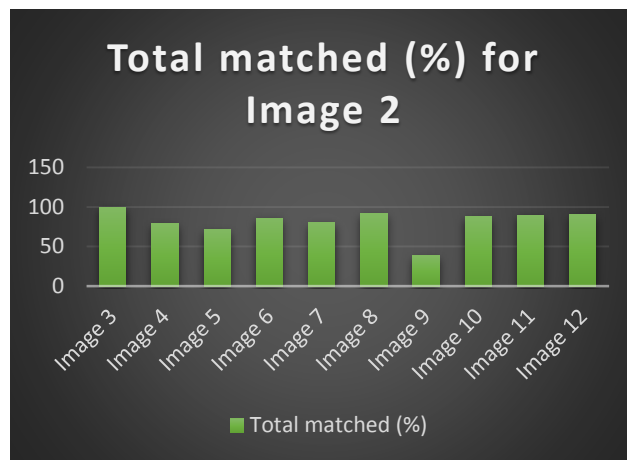


Figure 4.2(a): Matched (%) after pixel count

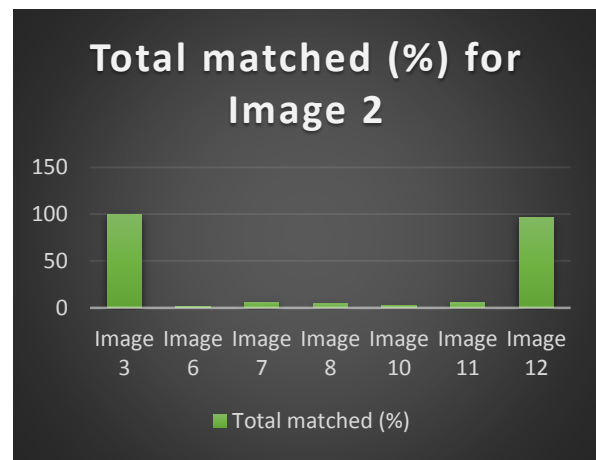


Figure 4.2(b): Matched (%) after SURF

Comparison: We tried to compare our accuracy level with another existing method. We have compared with Harris corner detection algorithm. Because, Harries algorithm contains completely different way of extraction method than our proposed algorithm [17]. We have worked with few datasets that we used in our algorithm and tried to show the difference in accuracy level. Table 4.2 shows the results found. The images belong to the same person with only the minor difference in the image panning and angle.

Serial No.	Image for identification	Image from Dataset	SURF Algorithm	Harris Algorithm
1	Image 1	Image 4	100	36
2	Image 1	Image 6	100	86
3	Image 2	Image 12	97	0
4	Image 2	Image 3	100	65

Table 4.3: Comparison between SURF and Harris feature extraction

CHAPTER 05

Conclusion and Future Work

5.1 Conclusion

In this paper we are using three steps human identification algorithm for matching dental x-ray images. Firstly we segment the initial dental radiographic image based on the color information. Then we use Wiener method for reduce noise and make smooth image. Secondly, we have used canny edge detection algorithm to figure out the tooth edge. Then we have calculated pixel values of image. Thirdly, SURF algorithm is used for find the interest points. Paper addresses the problem of dental radiographic image shape extraction and matching technique. This will be beneficial for forensic dentistry to identify the missing person in some critical mass disaster situation. After analysis, it is determined that algorithm proved to be automatic, less complex and provide satisfying results. Our proposed model has provided above 90 percent accuracy.

5.2 Future Work

In this paper, we worked with few datasets of panoramic X-ray. In the future, we want to work with a large dataset because medical images are hard to collect. Also, we want to improve the accuracy of our current system and work on the other dental X-ray methods to get more accurate identification. Another of our future goal is to overcome the limitations present in our system. Lastly, one of the major problem in dental X-ray identification is detection of a person after dental surgery because at that point, the X-ray image undergoes a lot of changes.

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