Fuzzy Features for Facial Shape Classification on Panoramic Dental Image

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Abstract. Research on human face shape identification can assist forensic teams in reconstructing an unidentified victim’s facial features. Human face shape identification using panoramic dental imaging is suitable for use by forensic teams in identifying a large number of victims due to the teeth’s ability to withstand heat of up to 1,000°C. This study proposes an application for face shapes classification on panoramic dental image using fuzzy features and decision tree method. It will be used to assist forensic scientists in reconstructing unidentified people identifying numerous victims from their facial features. There are three classifications of human face shapes, namely oval, tapered, and square. The steps in this study are digitizing panoramic dental images into files; segmenting the upper jaw’s incisor teeth; then extracting the features by area, parameter, width, length, width-to-length ratio, area-to-parameter ratio, center_x and center_y. Fuzzy theory is used to convert numeric features into category features, while decision tree method will be used for training features. The experimental results show that the proposed method obtain accuracy 67% of 42 panoramic dental image.

1. Introduction

Forensic identification has been growing rapidly with a variety of science fields being implemented to solve an algorithm in order to facilitate in identifying a large number of victims of natural disasters or mass casualties. Forensic odontology identifies individuals based on their teeth. The reason for using forensic odontology is the teeth’s ability to withstand fires and heat.

Identifying individuals with panoramic dental imaging can be used as an alternative to determine a person’s sex, age, or forensic identification. Forensic identification is used to identify victims of crime or mass casualties. An advantage of using panoramic dental imaging is the tooth’s resistance to heat and can withstand temperatures of up to 1,000°C. Using panoramic dental imaging on mass victims can be done more efficiently compared to individual DNA testing.

Damaged bodies in accidents or disasters is relatively difficult to identify. The most accurate methods of identifying bodies in such cases are DNA testing and reviewing dental records. DNA tests
take a relatively long time to produce results, making dental records the better option. Having dental radiography records makes the person much more easily identifiable.

Identifying teeth can uncover age, sex, and can be used to reconstruct facial shape. The purpose of facial reconstruction using dental imagery is to identify victims when their corpses are not intact or damaged, and when the face is unrecognizable. Identification of human facial features is beneficial to reconstruct faces as well as identifying the shape of the face (oval, tapered, or round). This research is related to classifying human facial shape on dental panoramic image, where the face can be classified as either tapered, square or oval. This study proposes an application for face shapes classification on panoramic dental image using fuzzy features and decision tree method. Fuzzy theory is used to convert numeric features into category features, while decision tree method will be used for training features. It will be used to assist forensic scientists in reconstructing unidentified people identifying numerous victims from their facial features.

Decision tree is a tree where each internal node indicates an attribute test, each branch represents the test results, and the leaf nodes show the classes or class distribution [1]. Decision tree is a structured tree consisting of a set of attributes to be tested with the purpose of forecasting their results. It is one of the most popular tools in classification because the results can be understood in the form of decision rules. In determining which attribute must be tested first, we must look at the attribute with the highest gain. Decision tree attempts to find the appropriate attribute to complete and define the class. In other words, the uppermost attribute of the Decision tree is the most influential attribute in determining the predicted outcome. Therefore, the Decision Tree modelling process is an interactive process to assess the most influential attribute to branch off from the tree-like structure. The branching is also commonly referred to as the split point [2]. This process can be divided into two steps: calculating the magnitude of the influence of each attribute and choosing the most appropriate attribute to split from the tree structure. For the first step, there are several matrices that can be used to calculate the magnitude of influence such as entropy, information gain [2].

ID3 algorithm is a model used to generate Decision Trees. The input of ID3 algorithm is a database consisting of several variables, referred to as attributes. Each input in the database presents an object of a domain called an independent variable. An attribute is designed to classify an object called a dependent variable [2].

The algorithm process of ID3 [3] is: Input: Training samples, samples; Output: Decision Tree; Method: Create node N; (1) If samples are all of the same class, C then return N as a leaf node labeled with the class C; (2) If atribut-list is empty then Return N as a leaf node labeled with the most common class in samples; select test-atribut, atribut among attribute-list with the highest information gain; (3) Label node N with test-atribut; (4) For each known value a, of test-atribut: Grow a branch from node N for the condition test atribut ai; Let Si be the set of samples in samples for which test-atribut = ai; If Si is empty then Attach a leaf labeled with the most common class in samples; Else attach the node returned by Generate_decision_tree (Si,atribut-list-test-atribut).

Fuzzy logic was first developed by Prof. Lotfi A. Zadeh, a researcher from the University of California [4] who introduced the theory of Fuzzy and Fuzzy logic as a way of overcoming inaccuracy and uncertainty. Each member in the Fuzzy set has a membership value degree that determines whether a potential member can fit into a Fuzzy set. A Fuzzy set is a development of the classical logic that models everything using boolean terms (Yes and No, 0 and 1).

Research [5] proposed local fuzzy thresholding based on measuring fuzzy similarity in interactive segmentation of panoramic dental imagery. The proposed method [5] consists of three main stages:
region splitting to identify a local region, user marking to obtain the initial seed background and object, and measuring fuzzy similarity is each local region to obtain a threshold value. The results of the panoramic dental imagery test succeeded in segmentation with an average misclassification error (ME) of only 5.47 percent.

Forensic radiology is a part of forensic medicine, used to study the identification of humans through postmortem radiology images of various body parts such as the spine, skull, and teeth. Identification is done through comparing postmortem (PM) and antemortem (AM) records.

Research [6] diagnosed acute leukemia with the use of a Fuzzy Decision Tree. Fuzzy was used to process the input on a 0 to 1 scale. The results are used as a dataset Decision Tree. The process was for studying, which yielded a tree and rule, where that rule was used to diagnose the disease.

The Fuzzy method is used to classify teeth based on periapical radiography [7], where each analyzed tooth was based on a set of criteria, such as area-to-perimeter and width-to-height ratios. The tooth classification process used for this study is periapical radiography imaging. The proposed method of classification [7] is implemented as a submodule system in identifying individuals from the teeth of the lower jaw.

Identification is dental forensics is the application of all disciplines of dentistry related to an investigation in obtaining postmortem data, useful in determining authenticity and identity of the victim and suspect for the sake of law in a judicial process and upholding the truth [8]. The Naïve Bayes algorithm, Artificial Neural Network, and ID3 are all appropriate algorithms for classification. Evidence of accuracy of these logarithms can be found in [7,9]. The ID3 algorithm does an initial study, it then generates a Tree and Rule. We can prove a classification of an object using the resulted Tree and Rule.

Research [9] developed and established a system to identify the sex of an individual based on panoramic dental pictures. Research [9] used 20 panoramic photos of human teeth which was then digitized and used as input. Next, the pictures went through pre-processing, an enhancing of the pictures in order to give maximal yields. The feature extraction stage takes the most significant features of an image, such as the length of the mandibula, the length of the arch, and other attributes. The results of this stage were processed using backpropagation algorithm. The purpose of the testing phase was the determine accuracy of the system.

In study [10] computerized human face identification required high accuracy due to the actual 3D form of a human face and a computers limitation to 2D. Previous research also developed an application to restore a face as realistically as possible [10].

Research [11] discusses the problem of the 3D face rendering approach of occluding contour, which is the limits between the facial area and background. The purpose of [11] was to study the relationship between a 2D and 3D face shape using linear regression. [11] found the matrix approach in linear regression was able to estimate a 3D face shape from a 2D shape trained from the selected contour. The approach of [11] offered a differentiating face shape against a 2D and 3D picture.

Research [12] made an offline system used to identify a 3D face shape. The identification process of a face shape helped with reconstruction at an appropriately accurate level. Identification was based on robust estimation of albedo for illumination.

Study [13] focused on picture identification based on features. Preparation of feature were based on color, texture and shape. The color feature used a histogram picture, the texture feature used Gray
Level Co-occurrence Matrix (GLCM), and the shape feature used canny edge detection. Color, texture, and shape extraction techniques resulted in 18 usable features in the Clustering process of pictures in the following study. Testing methods included Purity and Precision of a picture against a group of practice pictures.

Edge detection [14] is finding a part of an image experiencing intensely drastic changes. There are two ways to find the parts, namely using the first instance (magnitude of intensity is greater than the defined threshold) and using the second instance (color intensity has zero crossing). In research [14], using Canny Edge Detection commonly uses the following algorithms: Smoothing to reduce the effects of noise on edge detection; Calculating the potential image gradient; Non-maximal suppression of the image gradient to precisely localize the edge; and Hysteresis thresholding for final classification. The next step was to calculate the edge direction histogram using five bin directions, namely 0°, 45°, 90°, 135°, and 180° with three similar pixels.

The feature used to identify the leaf type included shape, color, and texture. Not all features needed to be used to compute the extraction, but some features needed to be selected based on their significance of influence in the retrieval system of the leaf image [15]. Correlation-based Feature Selection (CFS) was used to select features based on their correlations between one another, increasing the performance of the retrieval system of the leaf image. Feature selection types used included CFS, CFS with Genetic Search (GS), and chi square. Analysis of correlations was done through a combination of selected features and counting the similarities with the retrieval system. Lp norm, manhattan, euclidean, cosine, and mahalanobis proximities were used. The results of [15] show that the retrieval value was highest when using CFS with measuring mahalanobis proximity. There were six types of features used, namely: slimness, the ratio between the length and width of the leaf; form factor/roundness, the area and circumference of the leaf; rectangularity, drawing similarities in shape with the leaf and a box shape; narrow factor, the ratio between diameter and length; the roving ratio, the ratio between the circumference (P) and diameter (D); the perimeter ratio, the ratio between length and width; and the width (Wp).

The purpose of this study is to classify human face shape using panoramic dental imagery with ID3 algorithm. This research is expected to help identify individuals based on their facial features, and prove the accuracy of ID3 algorithm in classifying face shape.

This research serves to help forensic teams in identifying victims or people from the shape of their faces. This application can help save time in identifying unidentified people when compared to DNA testing.

This article was organized into introduction, research methodology, results and discussion, and conclusion.

2. Research Methodology

The diagram system of this research can be seen in Figure 1. The steps for the Fuzzy and ID3 algorithms for this research are:

a) Panoramic dental images are enhanced using median filter
b) Thresholding using Iterative Adaptive Thresholding
c) Segmenting images of incisor teeth
d) Take features of panoramic incisor images
e) Feature value normalized using Fuzzy. Fuzzy graphic used in a membership set is triangular. The limits for the triangle are taken from the lowest of each feature, and the cap is the highest of each feature, and average of each feature.

f) Studying Decision Tree

g) Testing Rule

![Diagram of facial shape classification on panoramic dental image]

**Figure 1.** The diagram system of facial shape classification on panoramic dental image

Data used in this includes 26 panoramic images of teeth. Segmentation was done on the images to view the top incisor teeth, resulting in 52 incisors teeth. The panoramic images show the upper and lower jaws, and the only incisors used in this study are the ones located on the upper and lower jaw. The input data of the panoramic dental images are shown in Table 1.

| No | Panoramic Dental Images |
|----|-------------------------|
| 1  | ![Panoramic Dental Image](image) |
This research enhances the images and extracts the features. The fuzzification of the features are saved in the database. This study takes the panoramic dental data. After it is taken in the form of a panoramic radiographic scan, it is enhanced and segmented to take the incisors of the upper jaw. They are put in a median filter for enhancement. The median filter is done with iterative adaptive thresholding. The area, perimeter, length, width, area-to-perimeter ratio, width-to-length ratio, center_x, and center_y are taken. It is then fuzzified, with the fuzzification value entered into the dataset for ID3 training to generate a tree and rule. The tree and rule are then used to test the system.

The extracted features-starting from the area, perimeter, length, width, length, width-to-length ratio, area-to-perimeter ratio, center_x, and center_y-are normalized using fuzzification. The Fuzzy used is a triangular graphic shown in Table 2. The limits of the triangle are: a = lower limit taken from each feature; b = highest value taken from the average of each feature; and c = maximum value of each feature.

| Membership Features | Graphic |
|---------------------|---------|
| Area [3500 11750 20000] | ![Membership function plot](image) |
Perimeter [90 150 200]

Width [100 150 200]

Length [50 130 200]

W/D Ratio [1 2 3]

A/P Ratio [30 80 120]
Table 3 shows the initial data of the feature extraction of the panoramic dental image of the incisor teeth. Fuzzification is shown in Table 4. The data is saved to the database and the CSV file is converted to a descriptive value shown in Table 5.

**Table 3. Incisor Feature Values**

|     |     |     |     |     |     |     |     |     |     |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| A   | P   | W   | L   | W/L | A/P | C_x | C_y | Class |
|-----|-----|-----|-----|-----|-----|-----|-----|-------|
| 8090| 172 | 173 | 81  | 2.14| 47.03| 38.12| 71.01| Tapered|
| 6916| 156 | 157 | 65  | 2.42| 44.33| 35.18| 68.57| Tapered|
| 8404| 158 | 159 | 94  | 1.69| 53.19| 48.54| 69.92| Square |
| 6706| 149 | 150 | 79  | 1.90| 45.01| 37.86| 75.12| Square |
| 14854| 176 | 177 | 128 | 1.38| 84.40| 65.24| 79.43| Square |
| 15175| 184 | 185 | 120 | 1.54| 82.47| 61.52| 84.12| Square |
| 10115| 164 | 165 | 108 | 1.53| 61.68| 56.23| 69.30| Oval   |
| 9496 | 156 | 157 | 96  | 1.64| 60.87| 44.98| 67.79| Oval   |
| 8995 | 155 | 156 | 87  | 1.79| 58.03| 40.77| 75.51| Tapered|

**Table 4. Results of Fuzzy Extraction**

|     |     |     |     |     |     |     |     |     |     |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| A   | P   | W   | L   | W/L | A/P | C_x | C_y | Class |
|-----|-----|-----|-----|-----|-----|-----|-----|-------|
| 0.56| 0.56| 0.54| 0.39| 0.86| 0.34| 0.27| 0.76| Tapered|
| 0.41| 0.88| 0.86| 0.19| 0.58| 0.29| 0.17| 0.86| Tapered|
3. Results and Discussion

The results of each stage of this research are as follows:

a) Readings of the panoramic dental image is shown in Figure 2.(a)
b) Panoramic dental images are segmented, taking only the upper and lower incisors. This is shown in Figure 2.(b)
c) Figure 2.(c) is median filtered, shown in Figure 5. Binary process was done using iterative adaptive thresholding.
After binarization of the left and right incisors of the upper and lower jaw, the features taken are: area, perimeter, width, length, width-to-length ratio, area-to-perimeter ratio, center_x, and center_y. The features were put into a database and normalized using fuzzy and studying ID3 algorithm. Data used to analyze the ID3 algorithm to classify facial shape consisted of 42 rows. The initial data in the form of numbers can be seen in Table 3. Afterwards, this was normalized using fuzzy on a scale of 0 to 1 as seen in Table 4 and convert to category as seen in Table 5. The normalized data shown in the triangular format can be seen in Table 2. The data was then saved to the database. The researchers used two method models to analyze the ID3 algorithm: the first had nine columns, which included area, perimeter, width, length, width-to-length ratio, area-to-perimeter ratio, center_x, center_y, and facial shape; the model had using ID3 algorithm.

The Tree for the model using ID3 algorithm. It resulted in the following rules:

1. if ratio_w/l=wide and length=wide and ratio_are/per=wide and perimeter=wide and centroid_x=wide then face=oval
2. if ratio_w/l=wide and length=wide and ratio_are/per=wide and perimeter=wide and centroid_x=narrow then face=oval
3. if ratio_w/l=wide and length=wide and ratio_are/per=wide and perimeter=narrow then face=square
The Rule of ID3 model resulted in eleven rules with an accuracy of 67 %, as seen in Figure 3.(a). The accuracy of both models ID3 algorithm is shown in Figure 3.(b), there are nine columns used or variables. Figure 3.(b) shows the variables used for model in Weka with nine column. The results for facial shape classification shows 28 correct rows of data from the dataset of 42 using ID3 algorithm. Testing of classifications can be seen in Figure 3.(c). The results of the facial shape classification showed that 28 rows of data were correct out of the 42 in the dataset, meaning an accuracy of 67 % using ID3 algorithm.
4. Conclusions

This study proposes an application for face shapes classification on panoramic dental image using fuzzy features and decision tree method. Fuzzy theory is used to convert numeric features into category features, while decision tree method will be used for training features. From the experimental results, it can be concluded that the ID3 algorithm resulted in an accuracy level of 67%.

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