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Dental Biometric Identification Scheme Based on Complex Auto Regression Model-An Aid to Forensic Dentistry

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Abstract: Automating the Forensic dental identification process is receiving increased attention. The main role of dental forensic experts is to identify individuals using the information extracted from their dental characteristics especially during major catastrophes like tsunamis, fire-accidents where the conventional biometric traits are usually unavailable or completely destroyed. In this paper, a dental biometric identification scheme is presented that extracts dental features from mandible using orthopantomograms. This system first traces the outer boundary coordinates of mandible and obtains a time series from these coordinates. Complex Auto regression (CAR) model is fitted to the obtained time series to get the CAR coefficients, which represent the mandibular structure. These coefficients are subsequently used for identification of individuals using clustering. The experimental results indicate that the proposed scheme exhibits better performance at CAR order six with low equal error rate of 19.850, and top-1 retreival accuracy of 0.80, thereby establishing its use in forensic applications. It is to mention that the results obtained using mandible bone as biometric identifier are not only at par with those obtained using the teeth and dental work based identification schemes but also the use of mandible bone as a biometric identifier overcomes the limitations associated with the teeth and dental work based identification schemes.

Keywords: Dental Biometrics, Forensics, Mandible, Orthopantomograms, Lower Jaw Bone, Complex Auto Regression Model, Panoramic Dental Radiographs, Antemortem, Postmortem.

1. INTRODUCTION

Forensic dentistry [1] uses the skill of a dentist to identify individuals for whom conventional means of identification is not possible because of unavailability of conventional identification traits (fingerprints, face iris, palm print etc.) [2]. In such cases, manual comparisons are performed between ante mortem (AM) and the post mortem (PM) dental features for identification of individuals [3]. This process being manual, takes a lot of time. So, an identification system is needed that can automate the dental identification process for speeding up the identification of individuals especially in case of natural disasters and major catastrophes [4] like fire accidents, tsunamis etc.

Dental Biometry [5], [6] is used in forensic dentistry for person identification based on dental features [7] which are unique to each individual. These dental features are extracted from dental x-rays of individuals and include tooth contours, shape and size of teeth, spacing between neighboring teeth, facial bone, dental work information like bridges, implants, fillings, crown etc. For identification purpose, the post mortem dental radiographs are compared against the ante mortem record of individuals. Some facial bones and teeth are among the hardest tissues found in humans that can sustain very high temperatures [8] and thus are suitable candidates for use in forensic identification.

Dental Biometric systems have been of great importance for identifying the victims of mass disasters as the conventional biometric modalities [9] are mostly destroyed under such circumstances. The dental Biometric systems available mostly use teeth and dental work information for person identification. However, the teeth and dental work-based identification systems have certain shortcomings. Teeth can change appearance, can be extracted, or can be missing altogether and dental works can also be damaged or missing because of accidents that may occur after the AM records are taken.

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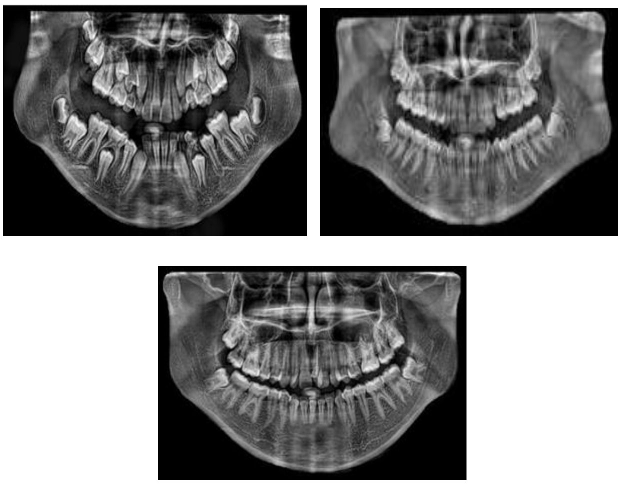


Figure 1. Orthopantomograms (OPGs) of three different persons.

Thus, an efficient and a strong biometric trait is required that can overcome the limitations associated with teeth and dental works. In this paper, mandible bone has been used as dental modality for person identification. Mandibular or lower jaw bone is naturally unique to each person [8], [10] and has the properties that it is resistant to high temperatures [11] and can also resist damage due to strong forces. Moreover, this bone has no fear of extraction, as is the case with teeth. The whole structure of mandible bone is clearly visible in panoramic radiographs commonly known as OPGs (Orthopantomograms) [12]. Therefore, OPGs are the best choice for identification using lower jawbone. Figure 1 shows OPGs of three different individuals and it can be seen that mandibular structures of all three individuals are distinct.

This paper is sectioned as: Section II explains some of the state of art dental identification techniques. Section III explains the proposed dental Identification scheme based on Complex Auto Regressive model, Section IV of the paper discusses the experimental results obtained. Finally, conclusion and the possible future work is discussed in the last section of this paper.

2. LITERATURE SURVEY

Most of the dental Biometric systems available, use teeth and dental work information [13] for biometric identification. Chen et al. [14], proposed a method for person identification using the contours of teeth extracted from dental radiographs. Teeth contours are extracted using active contour models and the information derived from these tooth contours is utilized for classification purpose. Mahoor et al. [15] proposed a dental identification method using bitewing x-ray images. They utilized Bayesian classification method to assign a specific number to each tooth. Nomir et al. [16], presented a human identification technique that uses shape and appearance of teeth in dental x-rays. The features are obtained using Fourier descriptors and a force-field function that represent the shape as well as appearance of the teeth. This method overcomes the limitation of utilizing the contour information of the teeth only which is very likely affected due to the low quality of some x-rays. Hofer et al. [17] have presented a method for person identification based on the information obtained from their dental works i.e spacing between neighboring dental works and their size extracted from panoramic radiographs. It uses snake algorithm for segmentation of dental works and finds the no of pixels between their centers of masses for distance calculation. In [18], Ghodsi et al. extracted teeth features from dental radiographs using Zernike moment which is rotation and scale invariant and then utilized Euclidian distance criteria to obtain a match score. Pushparaj et.al [19] extracts dental features from both radiographs as well as photographs of dental images. They have proposed teeth shape-based algorithm using both distance and skeleton measures for person identification and results obtained from dental x-rays are better than those obtained from dental photographs. Jaffino et.al [20] presented a technique for human forensic identification using information derived from dental works present in different radiograph images i.e, periapical, bitewing and panoramic dental x-rays. It uses Mahalanobis distance-based matching for victim identification. Rajput et al. [21] and presented teeth shape based matching algorithms using SBGFRLS based contour method and skeleton based methods. The performance measures reported are higher for skeleton method when compared to SBGFRLS based [22]method.

Different techniques have been used for extracting dental features from dental radiographs[23]. However, the time series model based techniques have not been explored much in dental biometry. It was Kashap and Chalpa [24] who first proposed the 2-D applications of modelling techniques. Dubois and Glanz [25] explored the use of modelling methods to represent the shapes of multiple patterns. Mir et.al [26] used Auto regression and Complex Auto regression (CAR) models for description of human organ shapes in radiographs. Khursheed et al. [27] used the time series model for recognition of humans using Ear as biometric trait.

From the literature, it is observed that most of the work in dental identification [28] is inclined toward the use of teeth and dental works as biometric identifiers and no attention has been paid towards the use of mandible bone as a biometric identifier, which is an actively used identifier used by forensic experts for human identification, though not automated [29]. Also, from the literature we conclude that a scope exits to explore usefulness of model-based methods for recognition of a person using their dental characteristics. In this paper, time series based Complex Auto Regression (CAR) model [25] is used and the time series [27] to fit the model is obtained from the mandibular bone structure for identification purpose. The quantitative analysis of this technique shows satisfactory results for identifying individuals.

3. DENTAL BIOMETRIC IDENTIFICATION SCHEME USING COMPLEX AUTO REGRESSION (CAR) MODEL

The proposed method explores the effectiveness of the Complex Auto Regression (CAR) model [26] in identifying individuals using mandibular bone shape as a biometric identifier. Panoramic dental radiographs (OPGs) are used in the proposed scheme for design of the biometric identification system, as whole structure of mandible bone is clearly visible in panoramic radiographs. The panoramic dental image database consisting of 210 OPGs obtained from 30 different persons in seven different positions is collected from a dental clinic. These radiographs contribute to the ante mortem (AM) as well as the post mortem (PM) record.

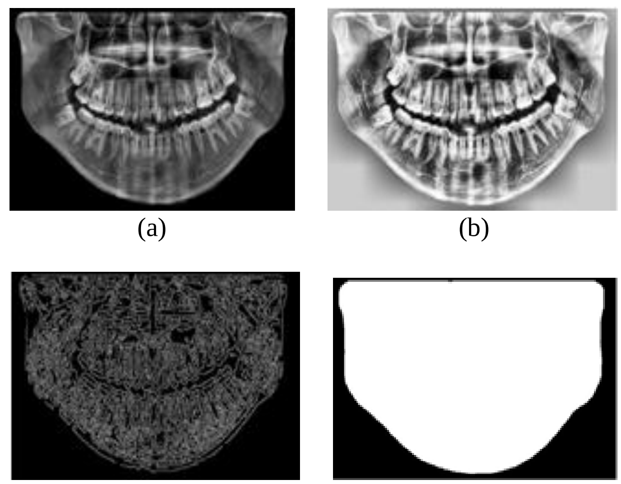
Mandibular bone is segmented out from the dental OPGs in order to obtain outer mandibular boundary points, which depict the structural information of mandible. These contour coordinates obtained from mandible represent the time sequence to which the CAR model is fitted for person identification. The coefficients thereby obtained from CAR model form the feature vector representing the mandible structure. The obtained feature vectors are then stored for matching, [18], [30] using Euclidian distance classification technique. The methodology of the proposed technique involves following three main processing steps:

a) Preprocessing of dental radiographs and mandible segmentation.
b) Feature extraction using CAR based technique.
c) Matching and Subject Identification.

A. Pre-processing of dental radiographs and mandible segmentation.

Radiographic images are susceptible to noises that occur at the time of acquisition of x-rays images. The quality of these images is improved [31] using clip limit adaptive histogram equalization process [32] followed by median filtering having kernel size 3. This process sharpens the x-ray image and improves the contrast making it suitable for the segmentation process. Figure 2 (a) and (b) show the original and the pre-processed radiograph.

A series of mathematical morphological operations are performed on the processed radiograph to segment the mandible bone, which is desired region of interest. In order to segment the image regions, edge detection technique is used. Among many edge detection techniques present, canny edge detection method is considered as the standard technique [32]. Canny's method [33] uses the first derivative of Gaussian (DoG) filter and double thresholding to provide good and reliable detection. This edge detection technique is thus applied on the pre-processed OPGs in order to segment out the outer mandible



(a) (b) (c) (d)

Figure 2. (a) Original Radiograph (b) Pre-processed Radiograph (c) Edge Detected Image (d) Segmented Image

bone shape as shown in figure 2(c). The edge images thus obtained have many disconnected edges. So, in order to prevent any loss of structural information, a series of morphological operations [34] are performed on the edge images. These include 'bwperim operator', 'flood fill' operator and 'closing operators' (dilation and erosion) which help in filling the disconnections to perfectly segment the outer mandible structure as depicted in figure 2(d).

B. Feature extraction using Complex Autoregression (CAR) model.

Time series is a sequential set of recordings of stochastic processes, typically measured over successive time and ordered chronologically. Time series models are used to make sense of the time series as the models are fitted to such observations for predictive forecasting [25], [26]. There are two broad categories of linear time series models. They are Autoregressive models and Moving Average models. The most commonly used models for shape description are the auto regression models and such models are also independent of rotation, translation and choice of the initial point.

This paper proposes the use of Complex Auto regression (CAR) model for mandibular shape description and presents a scheme for person identification using the same. Many 2-D applications of modelling techniques to represent the shapes of multiple patterns have been used in the literature [24], [25]. For obtaining the geometric description of 2-D patterns or objects in images, the boundary coordinates of objects in images represent the time sequence to which the CAR model fits. Thus, the CAR coffecients extracted from the CAR model represent the structural information of the object. The same 2-D CAR model [25], [26] concept is used for obtaining the time series from the bounding curve of mandible that is used to fit the CAR model in order to extract the CAR Coefficients which forms the feature vector [35] representing the mandible structure. Therefore, the first step is to trace the outer mandible boundary so as to obtain the time series in terms of its shape parameters.

1) Boundary Representation: The image obtained after segmentation undergoes boundary tracing. The boundary-tracing algorithm first determines the pixel coordinates which mark the beginning of gray level transition in the binarized segmented mandible image.

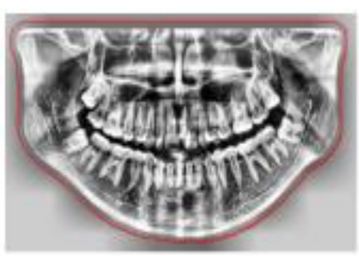


Figure 3. Mandibular Boundary Representation

These coordinates are used as an initial point for tracing the outer boundary of mandible. The detected mandibular contour as shown in figure 3 thus consists of a sequence of X boundary points, which form the shape parameters to fit the CAR model.

2) CAR Coefficients/Feature Vector Determination: Sequence of time series for CAR model is derived from traced mandible contour points $(x_j, y_j), \{j = 1,2, \ldots X\}$. The time series for CAR model constitutes of an ordered set of complex numbers, $z_j = x_j + iy_j, \{j = 1,2, \ldots X\}$ formed from X boundary points (Mir et.al). Thus, the CAR model of order ν is fitted to the sequence of these complex numbers $(z_1, z_2, \ldots z_X)$ and is represented by the following equation:

$$z_j = \sum_{k=1}^{\nu} b_k z_{j-k} + \epsilon_j \qquad (1)$$

where, $b_k, \{k = 1,2 \ldots \nu\}$ are the CAR coefficients; z_j is the time sequence under investigation and ϵ_j is the complex error.

The coefficients of CAR model $\{b_k\}_{k=1}^{\nu}$ are determined by minimizing the mean square error $\varepsilon^2(\nu, b)$ given as:

$$\varepsilon^2(\nu, b) = E_j(\bar{\epsilon}_j\ \epsilon_j) = b^* R(\nu) b - r^* b - b^* r + r_0 \qquad (2)$$

where,

$$R(\nu) = \begin{bmatrix} r_0 & \bar{r}_1 & \bar{r}_2 & \cdots & \bar{r}_{\nu-1} \\ r_1 & r_0 & \bar{r}_1 & \cdots & \bar{r}_{\nu-2} \\ r_2 & r_1 & r_0 & & \bar{r}_{\nu-3} \\ \vdots & & & \ddots & \vdots \\ r_{\nu-1} & r_{\nu-2} & r_{\nu-3} & \cdots & r_0 \end{bmatrix}$$

$$b = [b_1\ b_2\ b_3\ \ldots\ b_\nu]';$$
$$r = [r_1\ r_2\ r_3\ \ldots\ r_\nu]';$$

the sign * denotes complex conjugate transpose and r_k is complex autocorrelation coefficient given by:

$$r_k = E_j(\bar{z}_{j-k}\, z_j)$$

and $R(\nu)$ is Hermitian matrix ($R^*(\nu) = R(\nu)$)

Thus, CAR coefficients b_k are obtained by solving the following equation wherein the mean square error given in equation 2 is minimized.

$$b = R^{-1}(\nu)\ r \qquad (3)$$

and the least mean square error is:

$$\hat{\varepsilon}^2(\nu) = r_0 - r^* b \qquad (4)$$

CAR coefficients b_k, thus obtained form the feature vector representing the structural information of mandible in panoramic dental radiograph (OPGs) [36]. This structural information obtained from mandible is unique to every individual and is thus represents the dental biometrics of a person used for person identification.

C. *Matching and Subject Identification*

The extracted CAR features from the ante mortem (AM) radiographs of all the subjects in the database are stored in the AM record. Then, intra-class (Genuine) and inter-class (impostor) matching is performed on these stored features in AM record using Euclidian distance classification technique [37]. Based on this matching, a validation curve is plotted with the help of which threshold is set.

When a post mortem (PM)/query image is fed to the system, it undergoes similar feature extraction steps and the extracted CAR features from the PM x-ray images are matched with those of ante mortem (AM) x-ray images in the AM record. If the PM and the AM features in the record differ more than the set threshold, then output is 'Mismatch' otherwise it is a 'Match'. This completes subject verification.

The next step after verification is the subject identification. Subject identification is performed using clustering and the number of clusters C^s, $(s = 1,2, \ldots N)$ formed are equal to the subjects enrolled (N). Each cluster is tagged with the mean of cluster that represents a particular cluster/class. Here the cluster mean (C_v^s) is the mean of AM feature vectors (FV) of a particular subject given by:

$$C_v^s = \frac{1}{n_s}\sum_{r=1}^{n_s} F_r \qquad (5)$$

where, number of subjects $s = 1,2, \ldots N$, n_s is the number of ante mortem feature vectors (FV) that form a cluster representing a particular subject s, and F_r is the feature vector of rth antemortom radiograph of a subject (s) in the record.

During identification, the Euclidian distance [37] is calculated between query image (I_{PM}) and each cluster (C_v^s). Lastly, the query image is assigned to the cluster/class wherewith the distance obtained is minimum and this completes the identification process.

4. EXPERIMENTAL RESULTS

The panoramic dental dataset to assess the performance of the proposed biometric identification scheme includes 210 radiographs obtained from thirty subjects in seven different postures (-10^0, -5^0, -3^0, 0^0, 3^0, 5^0, 10^0). Out of these 7 instances of each subject, four radiographs at positions 0^0, 3^0, 5^0,-10^0 are used in training and are stored as ante mortem record. Rest of the subject instances at angles, -3^0, -5^0 and 10^0 are kept for PM testing.

A. Validation

Matching is performed by comparison of the intra-class (Genuine) and inter-class (Impostor) feature vectors in the record in order to obtain genuine and imposter distances. This is done using the Euclidian distance (ED) matching criteria.

A validation curve is obtained from these genuine and impostor distances and this curve shows little overlapped portion as shown in figure 4 which validates functioning of the algorithm. Then, based on this overlap, a threshold value is set that separates these classes.

B. Quantitative Analysis

For the performance assessment of the proposed identification scheme, test set of 90 post-mortem x-ray images is matched with the AM (ante mortem) record so as

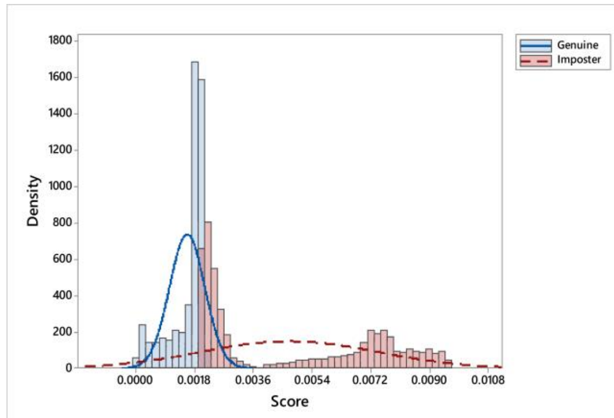


Figure 4. Validation Curve (Order 6)

to get genuine-test (intra class) and the imposter-test (interclass) distances. In case the distance between the compared feature vectors in the test Genuine class is more than set threshold, then output is considered as 'mismatch' otherwise output is a 'match'. Then, based on total matches and mismatches, GAR (genuine acceptance) and FRR (false rejection) are evaluated from test genuine class. Same thing also follows for the test imposter class and the genuine Rejection rate (GRR) and false acceptance rate (FAR) are calculated from the test imposter class [38].

The performance parameters [38] used for the assessment of the proposed technique include:

- FAR (False Acceptance Rate):
  $$FRR = \frac{Falsely\ Accepted\ Samples}{Total\ Imposter\ Samples}$$
- FRR (False Rejection Rate):
  $$FRR = \frac{Falsely\ Rejected\ Samples}{Total\ Genuine\ Samples}$$
- GAR (Genuine Acceptance Rate):
  $$GAR = \frac{Genuinely\ Accepted\ Samples}{Total\ Genuine\ Samples}$$
- RR (Recognition Rate):
  $$RR = \frac{GAS + GRS}{Total\ Samples\ Tested}$$

Other performance measures that have been used for the analysis of the results are EER (Equal error rate), ROC

(Receiver operating characteristic Curve) and Cumulative Match curve (CMC) [39] which have been explained in the subsequent part of this section.

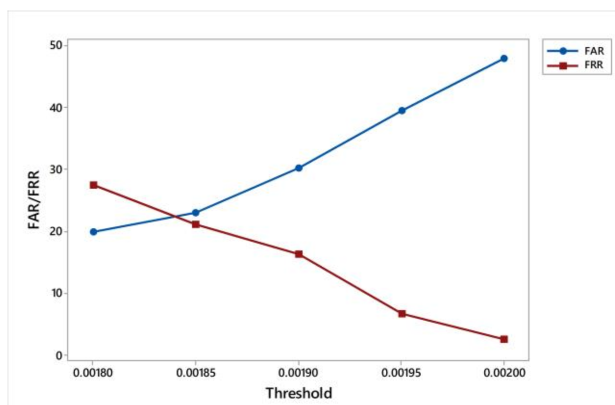
The performance of the proposed biometric dental identification scheme has been summarized in table 1. The

TABLE I. FAR, FRR AND RR AT DIFFERENT THRESHOLD VALUES FOR THREE DIFFERENT ORDERS OF CAR

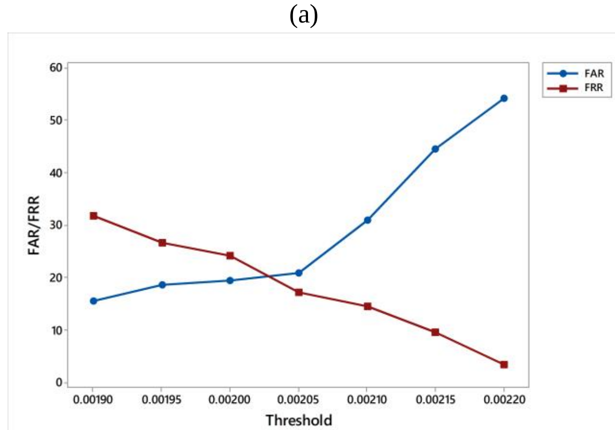
Order -3				Order -6				Order -10			
Threshold	***FAR***	***FRR***	***RR***	***Threshold***	***FAR***	***FRR***	***RR***	***Threshold***	***FAR***	***FRR***	***RR***
0.001800	19.89	27.50	79.87	0.001900	15.54	31.67	83.92	0.002050	15.90	30.28	83.62
0.001850	22.97	21.11	77.08	0.001950	18.56	26.67	81.24	0.002100	16.52	28.33	83.08
0.001900	30.26	16.39	70.20	0.002000	19.30	24.16	79.83	0.002150	19.11	23.33	80.75
0.001950	39.52	6.67	61.57	0.002050	20.87	17.22	79.25	0.002200	21.17	18.89	78.89
0.002000	48.06	2.50	53.45	0.002100	30.99	14.44	69.55	0.002250	32.52	11.39	68.18
-	-	-	-	0.002150	44.46	9.44	56.70	0.002300	49.35	4.72	52.14
-	-	-	-	0.002200	54.25	3.33	47.44	-	-	-	-

quantitative performance of the proposed method has been evaluated at different thresholds for various CAR orders and typical results at CAR orders 3, 6 and 10 are given in table 1. From table 1, it can be seen that proposed method shows satisfactory results at threshold values 0.001850, 0.002050 & 0.002200 for CAR-orders three, six and ten respectively. At threshold value 0.002050 of CAR order 6, the proposed technique has a minimum FA value of 20.87%, FR value of 17.22 % and a recognition rate (RR) of 79.25 %, which is better than that achieved with other CAR-orders.

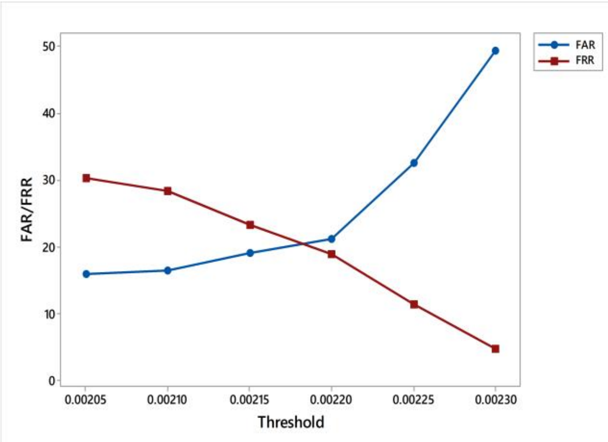
Equal Error Rate (EER) curve [38] is a plot between FAR and FRR values and is given by the intersecting point between FA and FR plots for a range of threshold values. The equal error rate curves for the proposed scheme at CAR orders 3, 6 and 10 are shown in figure 5. From these plots, it can be observed that equal error rates of 22.50%, 19.85% and 20.50% are obtained at CAR orders 3, 6 and 10 respectively. Lower the equal error rate better is the biometric system performance. As, the proposed system shows a low equal error rate (EER) value at CAR order 6, thus performs better at order 6 compared to the performance at orders 3 and 10.



(a)



(b)



(c)

Figure 5. EER Curves at different CAR orders: (a) 3- order (b) 6-order (c) 10-order.

Figure 6 shows ROC (receiver operating curves) characteristics [39] of the proposed method, which plots false acceptance (FA) values and genuine acceptance (GA) values generated at three different CAR-orders i.e. 3, 6 and 10. An ideal identification system yields a value at the upper-left-corner of ROC plot and that represents perfect recognition accuracy [39]. The ROC curves obtained using the proposed method indicate that ROC curve at order 6 of the CAR model yields a point closer to the 100 at the upper left corner as compared to that of other orders under observation. Therefore, the outcome of such assessments indicates that the proposed biometric identification system, using mandible as a biometric identifier shows highest recognition performance at CAR order-6 relative to other orders under observation.

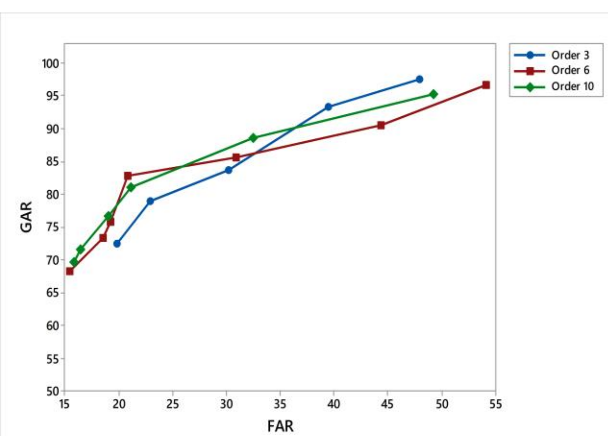


Figure 6. ROC characteristics at CAR-orders 3, 6 and 10.

C. Person Identification

During person identification task, the person in the PM query sample (probe) is identified if the PM sample is determined to be in the ante mortem repository. Identification/Hit rate is the likelihood that the person is correctly identified by the system at rank k.

Identification rate is calculated by using clustering. Euclidian Distances [40] between the determined query sample and all cluster-means is obtained and the subject in the probe is then assigned to the cluster/class wherewith it exhibits the least distance. Each test in the test set is assigned a rank based on the assigned class hierarchy and the rate at rank 1 is considered as the best identification rate.

TABLE II. COMPARING THE PROPOSED DENTAL IDENTIFICATION METHOD WITH STATE OF THE ART SCHEMES

Method	Dental Biometric Feature	EER (%)	RR (%)	Hit Rate Top-1 Retrieval
Proposed method	Mandible jaw bone	19.05	79.3	0.80
Chen et al. [14]	Tooth Contour	--	--	0.76
Hofer et al. [17]	Size, Position and distance between dental works	11.0	--	0.86
Nomir et al. [16]	Shape and appearance of Teeth.	--	--	0.85
Barboza et al. [41]	Shape of teeth	14.0	--	55.0
Ghodsi et al. [18]	Zernike Moment based Teeth numbering	--	--	0.81
Pushparaj et al. [19]	Skeleton and contour of teeth	--	--	0.77
Karunya et al. [42]	Tooth contours	--	--	0.72
Rehman et al. [43]	Teeth intensity profiles	--	--	0.85
Oktay et al. [36]	Position and Localization of dental works and teeth	--	--	0.81
Wang et al. [44]	Structure of Teeth	--	--	0.41
Gurses et al. [12]	Similarity of tooth pairs using SURF	--	--	0.80

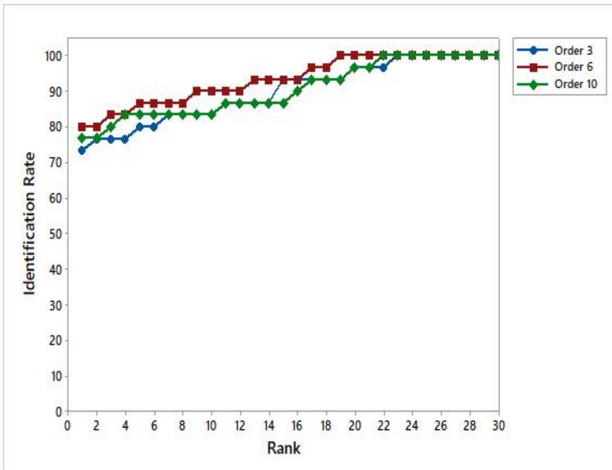


Figure 7. CMC Curves at CAR orders 3, 6 and 10.

Cumulative Match Curve (CMC) [39] is a characteristic plot between ranks and identification rates. Figure 7 shows three accuracy curves acquired from identification tests performed with three different CAR-orders on thirty PM image samples of different subjects. The rank~1 identification accuracy of the proposed identification scheme at CAR order-6 is 80 % and retrieval accuracy is 100 for top-19 retrievals. Also, rank 1 identification-rate of the proposed system at CAR-orders 3 and 10 are 73.33 % and 76.67% respectively. After the visual assessment of these CMC curves, it is clear that the proposed system shows better identification performance at CAR order-6 as compared to other CAR-orders (3 and 10) under observation.

A comparison of the proposed identification technique that uses mandible bone as biometric identifier with the state of the art identification methods using other dental characteristics like teeth and dental works has been shown in tabular form in Table II which depicts that results using the proposed scheme are better than most of the existing methods which also use very less test radiographic images for experimentation. Also, it can be observed that most of the work carried out in dental biometrics is either on teeth or on dental works and very less attention has been paid towards using mandible bone as biometric identifier. From the table it is clear that recognition and identification results obtained using mandible bone are at par with those obtained using the teeth and dental work based identification techniques and also it is to mention that the current experimentation has been performed on a larger database as compared to that used in the state of the art dental identification schemes.

5. CONCLUSION

Dental Biometry is receiving increased attention specially to identify victims of mass disasters, severe accidents and fire incidents where conventional biometric traits are unavailable. Dental biometrics uses information extracted from the dental radiographs of individuals for identification. This paper proposes an automatic dental identification system for smart cities, which extracts CAR features from mandibular contour in panoramic dental radiographs (OPGs) to identify persons. This method also overcomes the problems encountered with dental work and teeth based biometric systems. Experiments prove that the proposed CAR based dental biometric system exhibits suitable recognition and identification accuracy. The proposed system shows better results at CAR order six (6) with low equal error rate of 19.850, recognition rate of 79.250 and rank one identification rate of 80.00 as compared to other orders (3 and 10) under observation.

Though the propound method shows a satisfactory recognition and identification performance, however, there is scope for further improvement. More work needs to be done to overcome challenges in this rapidly evolving dental biometrics field. The challenges include: assessment of the proposed technique on a large database; exploring potential of other time series models and enhancing the recognition and identification rates further. The findings in this paper will significantly help dental forensic experts for identification of individuals and will save the time of odontologists.

REFERENCES

[1] D. R. Senn and P. G. Stimson, Eds., Forensic Dentistry, 2nd ed. CRC Press, 2010.
[2] K. Ito and T. Aoki, “Recent Advances in Biometric Recognition,” vol. 6, no. 1, pp. 64–80, 2018.
[3] V. Chandran and P. Simon, “Review on dental image based biometric system,” Proc. Third Int. Conf. Adv. Informatics Comput. Res., pp. 1–6, 2019.
[4] S. Sengupta, V. Sharma, V. Gupta, H. ; Vij, R. Vij, and K. Prabhat, “Forensic odontology as a victim identification tool in mass disasters: A feasibility study in the Indian scenario,” J. Forensic Dent. Sci., vol. 6, no. 1, p. 58, 2014.
[5] M. L. Leo, A. Shifani, and J. A. Simla, “A Review On Dental Biometrics From Various Images Based On Shape And Appearance Of The Teeth,” Res. J. Pharm. Biol. Chem. Sci., vol. 10, no. 1, pp. 1056–1063, 2019.
[6] M. Banday and A. H. Mir, “Cancellable biometric system based on linear combination of trigonometric functions with special application to forensic dental biometrics,” Int. J. Biom., vol. 11, no. 4, 2019, doi: 10.1504/IJBM.2019.102863.
[7] J. Am Dent, “Body Identification Guidelines,” Am. Board Forensic Odontol., vol. 125, no. 9, pp. 1244–6,1248,1250, 1994.
[8] M. Hofer and A. N. Marana, “Dental biometrics: Human identification based on dental work information,” Proc. SIBGRAPI 2007 - 20th Brazilian Symp. Comput. Graph. Image Process., no. June, pp. 281–286, 2007, doi: 10.1109/SIBGRAPI.2007.9.
[9] K. Kumar, H. Kumar, H. P. Singh, A. Kumar, and K. M. Shikha, “Biometric Security System for Identification and Verification,” Int. J. Sci. Res. Comput. Sci. Eng., vol. 8, no. 1, 2020.

[10] M. Banday and A. H. Mir, "Forensic dental biometry-a human identification system using panoramic dental radiographs based on shape of mandibular bone," Int. J. Biom., vol. 10, no. 4, pp. 291–314, 2018, doi: 10.1504/IJBM.2018.095284.

[11] S. T. D. Ellingham, T. J. U. Thompson, M. Islam, and G. Taylor, "Science and Justice Estimating temperature exposure of burnt bone — A methodological review," Sci. Justice, 2014, doi: 10.1016/j.scijus.2014.12.002.

[12] A. Gurses and A. . Oktay, "Human Identification with Panoramic Dental Images using Mask R-CNN and SURF," 5th Int. Conf. Comput. Sci. Eng. (UBMK), Diyarbakir, Turkey, pp. 232–237, 2020.

[13] P. L. Lin, Y. H. Lai, and P. W. Huang, "Dental biometrics: Human identification based on teeth and dental works in bitewing radiographs," Pattern Recognit., vol. 45, no. 3, pp. 934–946, 2012.

[14] H. Chen and A. K. Jain, "Tooth contour extraction for matching dental radiographs," Proc. - Int. Conf. Pattern Recognit., vol. 3, no. 1, pp. 522–525, 2004, doi: 10.1109/ICPR.2004.1334581.

[15] M. Mahoor and M. A. Mottaleb, "Classification and numbering of teeth in bitewing dental images," Pattern Recognition, IEEE, vol. 38, pp. 577–586, 2005.

[16] O. Nomir and M. Abdel-Mottaleb, "Human identification from dental X-ray images based on the shape and appearance of the teeth," IEEE Trans. Inf. Forensics Secur., vol. 2, no. 2, pp. 188–197, 2007, doi: 10.1109/TIFS.2007.897245.

[17] M. Hofer and A. N. Marana, "Dental biometrics: Human identification based on dental work information," Proc. SIBGRAPI 2007 - 20th Brazilian Symp. Comput. Graph. Image Process., no. Dc, pp. 281–286, 2007, doi: 10.1109/SIBGRAPI.2007.9.

[18] S. B. Ghodsi and K. Faez, "A novel approach for matching of dental radiograph image using Zernike moment," CSAE 2012 - Proceedings, 2012 IEEE Int. Conf. Comput. Sci. Autom. Eng., vol. 3, pp. 303–306, 2012, doi: 10.1109/CSAE.2012.6272960.

[19] V. Pushparaj, U. Gurunathan, and B. Arumugam, "Dental radiographs and photographs in human forensic identification," IET Biometrics, vol. 2, no. 2, pp. 56–63, 2013, doi: 10.1049/iet-bmt.2012.0047.

[20] G. Jaffino, A. Banumathi, U. Gurunathan, and J. Prabin Jose, "Dental work extraction for different radiographic Images in human Forensic Identification," 2014 Int. Conf. Commun. Netw. Technol. ICCNT 2014, vol. 2015-March, pp. 52–56, 2015, doi: 10.1109/CNT.2014.7062724.

[21] P. Rajput and K. J. Mahajan, "Dental biometric in human forensic identification," Proc. - Int. Conf. Glob. Trends Signal Process. Inf. Comput. Commun. ICGTSPICC 2016, pp. 409–413, 2017, doi: 10.1109/ICGTSPICC.2016.7955336.

[22] P. L. Lin and Y. H. Lai, "An effective classification system for dental bitewing radiographs using entire tooth," Proc. 2009 WRI Glob. Congr. Intell. Syst. GCIS 2009, vol. 4, pp. 369–373, 2009, doi: 10.1109/GCIS.2009.390.

[23] M. Rychlik, A. Przystańska, L.-M. D, and M. Glapiński, "Biometric Dental Rosette - Introduction into New Method of Dental Identification," Int. Conf. Univers. Access Human-Computer Interact. Springer, Cham, pp. 226–236, 2015.

[24] R. L. Kashyap and R. Chellapa, "Stochastic models for closed boundary analysis: Representation and reconstruction," IEEE Trans. Inform. Theory, vol. IT-27, pp. 627-635., 1981.

[25] F. . Dubois, S.R. Glanz, "An autoregressive model approach to two dimensional shape classification," IEEE Trans. Pattern Anal. Mach. Intell., PAMI-, vol. 8, pp. 55–66.

[26] A. H. Mir, H. Hanmandlu, and S. N. Tandon, "Description of Shapes in CT Images," IEEE Eng. Med. Biol., no. i, pp. 79–84, 1999.

[27] F. Khursheed and A. H. Mir, "Time series model based personal verification using ear biometrics," Proc. - 4th IEEE Int. Conf. Comput. Commun. Technol. ICCCT 2013, pp. 264–268, 2013, doi: 10.1109/ICCCT.2013.6749638.

[28] I. J. Mohammad Ehtisham, Sheeba Nissar, Shahla Khan, Rehan Khan, Firdous Wani, "Role Of Forensic Dentistry In Human Identification: 'Evidence That Does Not Lie,'" J Dent Sci, vol. 1, no. 2, pp. 66–73, 2016, [Online]. Available: http://www.academia.edu/download/46904456/Final_Article.pdf.

[29] A. Heinrich, F. V. Güttler, S. Schenkl, R. Wagner, and U. K. M. Teichgräber, "Automatic human identification based on dental X-ray radiographs using computer vision," Sci. Rep., vol. 10, no. 1, pp. 1–13, 2020, doi: 10.1038/s41598-020-60817-6.

[30] H. Chen and A. K. Jain, "Dental biometrics: Alignment and matching of dental radiographs," IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 8, pp. 1319–1326, Aug. 2005, doi: 10.1109/TPAMI.2005.157.

[31] S. Gupta, R. Gupta, and C. Singla, "Analysis of image enhancement techniques for astrocytoma MRI images," Int. J. Inf. Technol., vol. 9, no. 3, pp. 311–329.

[32] R. C. Gonzales and R. E. Woods, Digital Image Processing. Pearson.

[33] E. A. Sekehravani, E. Babulak, N. S. Foundation, and M. Masoodi, "Implementing canny edge detection algorithm for noisy image Implementing canny edge detection algorithm for noisy image," no. February 2021, 2020, doi: 10.11591/eei.v9i4.1837.

[34] "Mathamatical Morphology," [Online]. Available: https://en.wikipedia.org/wiki/Mathematical_morphology .

[35] L. J. Joseph, L. B. George, G. Shabna, I. Susmi, and N. Santhi, "Teeth feature extraction and matching for human identification using morphological skeleton transform," 2016 Int. Conf. Energy Effic. Technol. Sustain. ICEETS 2016, pp. 802–807, 2016, doi: 10.1109/ICEETS.2016.7583857.

[36] A. B. Oktay, "Human identification with dental panoramic radiographic images," IET Biometrics, vol. 7, no. 4, pp. 349–355, 2017.

[37] "Euclidean Distance Raw, Normalized, and Double-Scaled Coefficients," Tech. White Pap. Ser., vol. 6, pp. 1–26, 2009.

[38] "Human Scan Gmb. About FAR, FRR and EER," 2007, [Online]. Available: http://www.bioid.com/sdk/docs.htm.

[39] A. Ross, "Relating ROC and CMC curves," 2016.

[40] P. Barrett, "Euclidean Distance Whitepaper," Tech. Whitepaper Ser. 6, p. 26, 2005, [Online]. Available: http://www.pbarrett.net/techpapers/euclid.pdf.

[41] E. B. Barboza, A. N. Marana, and D. T. Oliveira, "Semiautomatic dental recognition using a graph-based segmentation algorithm and teeth shapes features," Proc. - 2012 5th IAPR Int. Conf. Biometrics, ICB 2012, pp. 348–353, 2012, doi: 10.1109/ICB.2012.6199831.

[42] R. Karunya, A. Askarunisa, and A. Athiraja, "Human Identification Using Dental Biometrics," Int. J. Appl. Eng. Res., vol. 9, no. 20, 2014.

[43] F. Rehman, M. U. Akram, K. Faraz, and N. Riaz, "Human identification using dental biometric analysis," 2015 Fifth Int. Conf. Digit. Inf. Commun. Technol. its Appl. IEEE, pp. 96–100, 2015.

[44] L. Wang, J. Mao, Y. Hu, and W. Sheng, "Tooth identification based on teeth structure feature," 2020, doi: 10.1080/21642583.2020.1825238.

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