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Forensic Human Identification using Dual Cross Patterns of Dental Panoramic Radiographs

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Abstract

Dental biometrics plays a very vital role in identifying the victims in natural and human-made disasters. The survivability and diversity of dental radiographs make them excellent alternatives over traditional biometric techniques using fingerprints, face, and iris. The main focus of this study is to deal with missing and unidentified person identification from a guide to automated based on dental panoramic radiographs using Dual Cross Pattern features that are complicated to be assessed only by visual examination. This paper seeks to identify an appropriate classifier amongst Feedforward Neural Network (FNN), Multiclass Support Vector Machine (m-SVM), k-Nearest Neighbor (k-NN) and Classification Tree (CT) based on retrieval accuracy of 10 adult subjects with 100 panoramic radiographs. The preliminary results on a small dataset are encouraging.

Keywords

Forensic Science, Dual Cross Pattern, Ante-Mortem (AM) Radiographs, Human Identification, Classification, Postmortem (PM) Radiographs.

Introduction

In forensic radiography, the unlabeled post-mortem (PM) radiographs of the body including the skeleton, skull, and teeth of the deceased are compared with the ante-mortem (AM) records of a missing person to determine the similarities between them [1,2,3]. The recent catastrophes have shown how important it is to rely on biometric radiographs to attract public awareness. For instance, the activist assault in the United States on September 11, 2001 [2], 20% of 973 victims were identified in the first year using dental protocols [2]. A large number of victims from the Asian tsunami in 2004 were also identified based on dental information. In Thailand, 75% of tsunami fatalities were recognized based on dental radiographs, 10% from fingerprint records, and only 0.5% by DNA profiles [3.4]. For the identification of other victims, a combination of different techniques was used [4, 5].Radiographs have played a significant role in solving severe cases in forensic science [6,7,8]. Figure 2(a-c) explores most commonly used radiographs; the periapical, bitewing, and panoramic respectively. WinID [9,10] is dental software which has been demonstrated useful in major disasters and the creation and maintenance of individual databases [9,10]. The OdontoSearch 3.2 computer program provides a way to assess the frequency of dental procedures but cannot be used to find the identity of the victims [1,11]. Mahoor and Mottaleb [12] proposed Bayesian classification for bitewing radiographs using Fourier descriptors of contours based on universal numbering system used in dentistry. Jain and Chen [13] again developed a shape registration technique based on contours of teeth and dental work. Subjects were retrieved by matching tooth contours using a method of shape registration and on the overlapping work areas. Hofer and Marana [14] designed a human identification method based on panoramic dental radiographs by extracting &matching dental work of 22 PM radiographs with the 46 AM radiographs of the database. Nomir and Mottaleb [15] introduced a dental x-ray matching technique depends on Hierarchical chamfer distance algorithm. Nomir and Mottaleb [16] again introduced a technique using the fusion of matching algorithms for AM and PM radiographs by using tooth contour, hierarchical chamfer distance and combine features extracted from force field energy function and Fourier descriptors. For dental bitewing radiographs, an efficient classification system was proposed by Lin and Lai [17]. Lin and Kuo [18] used spatial domain features and frequency domain metric for matching PM image with positive AM image based on dental work. Harandi and Pourghassem [19] proposed low-level image processing techniques for measuring the length of the root canal. Oktay [20] proposed a probabilistic graphical model-based automatic human identification using panoramic radiographs. Ajaz and Kathirvelu [21] suggested a human identification technique using dental work from panoramic radiographs. Figure 1 represents sample pre-dental and post-dental work panoramic radiographs from dataset

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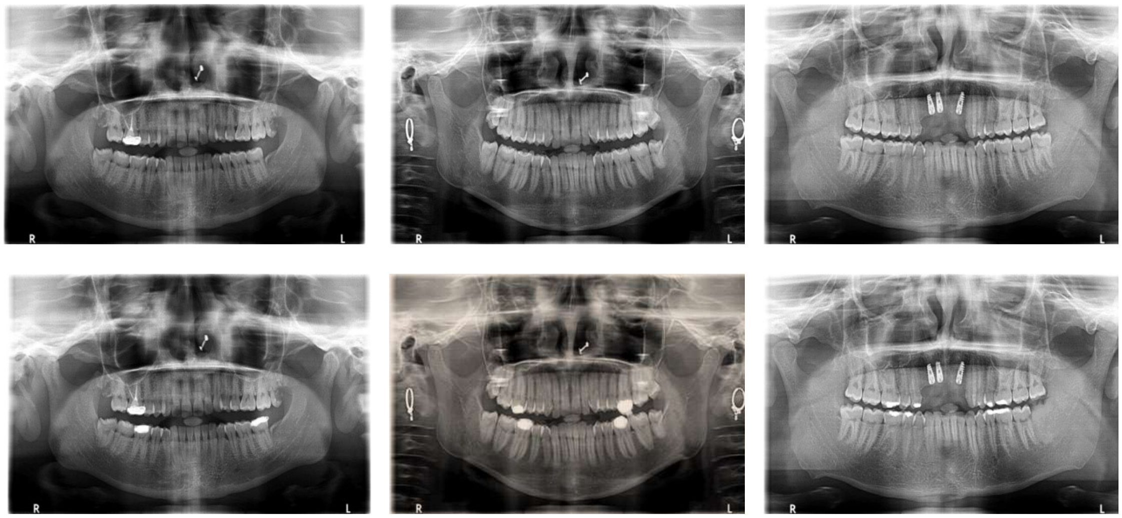

Fig. 1: Sample Panoramic Images from Dataset Captured at Different Time. Images in first row are the Pre- dental work and images in second row are Post-dental work images

Proposed System

The key advantage of the suggested method is to vanquish the segmentation concern encountered by state of art authors for teeth numbering system and identification of victims where traditional biometric techniques cannot be utilized. There are two stages involved in the human identification progression using dental panoramic radiographs (see Fig.2).When an image is entered into it, it can either be used to search for a neighboring record in the database or to build the database. In both cases, features are extracted from the image. After entries are made in the database, storing the extracted information is the last step of the process. At the time of retrieval, the final step is to compare all extracted data values from those records stored in the database. Pre-processing is generally helpful to remove blurring that is caused by both the machine as well as errors introduced by the individual while recording the panoramic image. It reduces the amount of speckle noise present in the image, which is a major problem encountered in radiographic images.

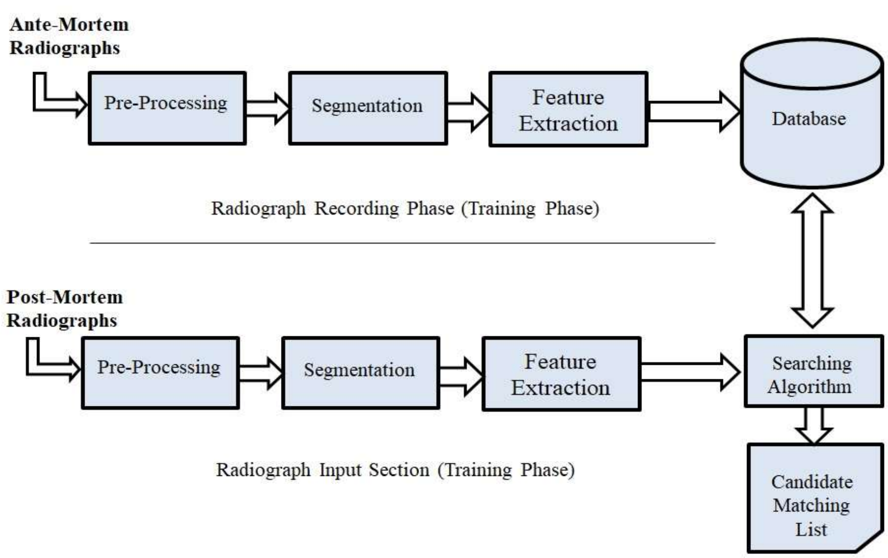

Fig. 2: General Architecture of Human Identification System Using Biometric Radiographs

1. Dual Cross Pattern (DCP) Feature Extraction

The three major steps in the development of the DCP image descriptor are image filtering, local sampling and pattern encoding. The key to DCP success is to execute pattern encoding and local sampling in the most descriptive direction

to encrypt second-order statistical information. In two stages the sampled points are encoded. Various Steps in DCP feature based image retrieval system is as follows:-
Step 1: Conversion of an input image into gray image
Step 2: Local Sampling: Carry out an eight-direction symmetrical sampling for each pixel of the image in the local neighborhood.
Step 3: Pattern Encoding: The textural data is quantized using pattern encoding in each sampling direction. For each image, two cross encoders generate the encoded images and derive the feature vector.
Step 4: Grouping: Combining feature vectors derived from two cross encoders.
Step 5: Comparison of query image feature vector with feature vector stored in database.
Step 6: The best matched images are recovered.

1.1 Local Sampling:

The center pixel $P_0$is computed by comparing its gray value with eight direction neighbors $(0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}, \pi, \frac{\pi}{4}, \frac{5\pi}{4}, \frac{3\pi}{2}, \text{and} \frac{7\pi}{4})$ to get necessary amount of texture information. Two pixels are sampled from each direction and are represented as $\{P_{A1}, P_{B1}; P_{A2}, P_{B2}; P_{A3}, P_{B3}; P_{A4}, P_{B4}; P_{A5}, P_{B5}; P_{A6}, P_{B6}; P_{A7}, P_{B7}; P_{A8}, P_{B8}\}$. $P_{A1}; P_{A2} \dots P_{A8}$are uniformly distributed on the inner radius R_A (See fig.3), similarly $P_{B1}; P_{B2} \dots P_{B8}$ are equally distributed on the inner radius R_B.

1.2 Pattern Encoding:

First, the texture details are encoded along each of the eight directions, which are followed by combining the pattern obtained for creating DCP code. A distinctive decimal number (See equation 1 and 2) is given in each sampling direction to quantize the textural information [22,23]. For the reduction of computational complexity, an exclusive grouping strategy is used in DCP. According to joint Shannon entropy, the total distinct levels in code will be too large for implementation, hence by grouping into two; each is called encoder, the total number of levels reduce to = 512 [22,23].

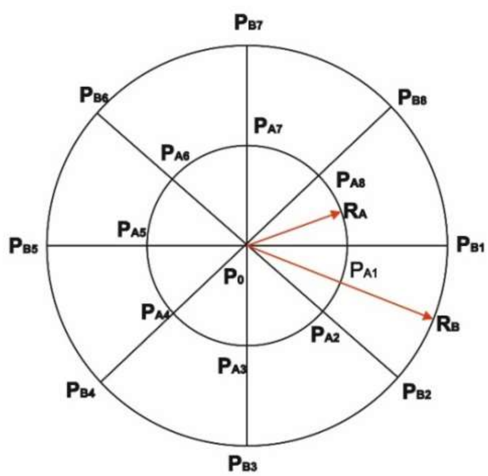

Fig.3: Local pixel sampling in DCP

$$\mathrm{DCPp} = \mathrm{D}(P_{A_i} - P_0) \times 2 + \mathrm{D}(P_{B_i} - P_{A_i}) \qquad 0 \le i \le 7 \tag{1}$$

$$\text{Where } ,D(x) = \begin{cases} 1, & x \ge 0 \\ 0, & x < 0 \end{cases} \tag{2}$$

1.3 DCP Grouping:

Applying grouping technique on eight directions a total of 35 combinations are produced. A joint Shannon entropy criterion is used [23] for an optimum grouping of eight directions to preserve information required for image recovery.

$$H(DCP_0, DCP_1, DCP_2, DCP_3) = -\sum_{\mathrm{dcp0}} \dots \sum_{\mathrm{dcp3}} \mathrm{P}\ (\mathrm{dcp}_0\ \dots \mathrm{dcp}_3) \log_2 \mathrm{P}\ (\mathrm{dcp}_0 \dots \mathrm{dcp}_3) \tag{3}$$

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Where, $(dcp_0 dcp_1, dcp_2, dcp_3)$ are particular values of $(DCP_0, DCP_1, DCP_2, DCP_3)$ respectively and $P(dcp_0 \ldots . dcp_3)$ is the Probability of $(DCP_0, DCP_1, DCP_2, DCP_3)$ values.The image is more independent of each other as the pixel are more scattered. Sample point separation with maximum distance result into maximum joint Shannon entropy in each subgroup [22][23].

$$DCP - 1 = \sum_{k=0}^{3} DCP_{2k} + 4^k \tag{4}$$

$$DCP - 2 = \sum_{k=0}^{3} DCP_{2k+1} + 4^k \tag{5}$$

The Final DCP descriptor of the image is formed by combination of DCP-1 and DCP-2 for every pixel

$$\mathrm{DCP} = \left\{ \sum_{\mathrm{k}=0}^{3} \mathrm{DCP}_{2\mathrm{k}} + 4^{\mathrm{k}}, \sum_{\mathrm{k}=0}^{3} \mathrm{DCP}_{2\mathrm{k}+1} + 4^{\mathrm{k}} \right\} \tag{6}$$

1.4 Panoramic Image Database & Influence of Block Numbers

In this paper, a total of 300 panoramic radiographs are collected from 30 adults including pre-dental work and post-dental work images at different head positions from Nidaan Diagnostics, Chinchwad, Pune, India. Keeping the head position fixed ensures a higher level of accuracy for experimentation purposes but not on a real-time basis. An attempt has been made to improve the accuracy level when matching is done on a real-time basis rather than to serve the experiment purpose solely. Out of the 30 adults, 10 adults are used for retrieval purpose (See table 1). The proposed system is implemented in MATLAB and executed on a computer with 3Gb RAM, Intel (R) Core 2 Duo processor, and WINDOWS 7 professional OS. Here, rather than selecting a single block per radiograph, the radiograph is divided into N blocks. The best descriptor of an image is achieved by selecting multiple blocks for local regions of the image. DCP feature vectors are calculated for block sizes 1x1, 2x2, 4x4, and 8x8, respectively, to study the influence of block size on retrieval accuracy and recognition time.

Table 1: Percentage Cross Validation Accuracy of DCP for Block Size N=1, N=2, N=3 and N=4. Red Value represents Incorrect Retrieval of Subject

Block Size (Feature Vector Length)	Name of Classifier	Cross Validation Accuracy in Percentage										Avg. Accuracy in percentage
		Subject										
		1	2	3	4	5	6	7	8	9	10	
N=1 (512)	k-NN (N=3)	90	50	70	80	50	70	80	50	60	40	64
	k-NN (N=5)	70	70	70	80	50	50	60	50	50	50	60
	CT	40	10	10	0	0	60	80	80	90	40	41
	m-SVM	100	20	50	40	40	100	10	40	100	90	59
	FNN	60	50	30	30	40	60	90	50	60	20	49
N=2 (2048)	k-NN (N=3)	90	90	80	90	80	80	90	90	80	80	85
	k-NN (N=5)	80	70	50	80	70	60	80	70	80	70	71
	CT	40	40	40	10	40	70	60	60	40	60	46
	m-SVM	100	90	100	40	30	0	0	40	90	100	59
	FNN	60	40	80	40	80	30	50	80	70	60	59
N=4 (8192)	k-NN (N=3)	90	80	80	90	90	90	90	90	90	90	88
	k-NN (N=5)	70	90	70	60	90	80	50	80	80	80	75
	CT	50	80	20	0	50	80	70	50	0	0	40
	m-SVM	100	90	100	100	100	60	80	50	90	90	86
	FNN	60	70	70	60	30	70	70	90	20	60	60
N=8 (32,768)	k-NN (N=3)	90	80	80	90	80	90	90	80	80	80	84
	k-NN (N=5)	80	90	80	80	80	70	70	70	70	70	76
	CT	20	50	40	20	30	40	10	10	20	70	31
	m-SVM	90	100	20	90	20	20	10	100	0	0	45

Experiment Results

The descriptor of DCP feature is extracted by merging DCP-1 and DCP-2 and used for the classification of 10 subjects (See table 1) using classifiers such as Multiclass Support Vector Machine (m-SVM), k-NN (N=3 and N=5), Classification Tree(CT) Classifier and, Feedforward neural network (FNN). By applying this, SVM along with the radial basis function, the kernel can be employed as one classifier. γ and C parameters, which employ a five-fold cross-validation process, are selected. One versus all SVM is used for multiclass classification as each potential subject denotes a new class since each subject holds unique features. The linear kernel is used for the class separating hyper-plane creation. SVM is trained for one against other class features. k-NN is the simplest classifier as it takes no time for training. Only the testing time is more as it finds the nearest neighbor using squared Euclidean distance. The FNN classifier used in this paper consists of 20 hidden layers. The scaled conjugate gradient method is used for training of the proposed neural network. The maximum number of training epoch used is 1000. The classifiers except m-SVM used in this study are reproducible from MATLAB inbuilt functions. The experimental results based on DCP feature vector of panoramic radiographs provide maximum retrieval accuracy level of 88% for a block size N=4 (feature vector length=8192) with k-NN (N=3), and 85% for a block size N=2 block size (feature vector length=2048) along with k-NN (N=3). The retrieval accuracy of DCP is minimized to 31% for N=8 block size (feature vector length=32768) with CT classifier.

Conclusion

The proposed technique is found to be suitable for the dataset of adults. Using DCP as a texture categorization method, human identification has been presented in this paper based on panoramic radiographs. The initial results on a minimum dataset indicated that dental panoramic radiographs are an appropriate approach for human identification. It is effortless and effective. Practically, it is indicated that by picking the suitable feature vector of an appropriate block size with acceptable classifiers can offer better texture categorization outcome. CT, m-SVM, FNN, and k-NN (N=3 and N=5) are the classifiers employed in DCP for human identification comparative study. Even though the proposed concept is easy, the experimental outcomes are favorable. It is evident that the result of this dental identification system is excellent. However, there is scope for future improvements. Future work will involve database extension of panoramic radiographs that servers various age groups and influences the complete performance of the proposed system. In future, to improve the pose correction, quality-based frame selection, and mark-based matching techniques can be combined to build a unified system based on panoramic radiographs.

Conflicts of Interest: None

References

[1] Manigandan, T., Sumathy, C., Elumalai, M., Sathasivasubramanian, S., & Kannan, A. (2015). Forensic radiology in dentistry. Journal of pharmacy & bioallied sciences, 7 (Suppl 1), S260.

[2] Forensic identification of 9/11 victims ends, New York, February 23, 2005.

[3] Jain AK, Flynn P, Ross AA, editors. Handbook of biometrics, Springer Science & Business Media, 2007 Oct 23.

[4] Hooper, R. (2005). Dental records beat DNA in tsunami IDs. New Scientist, 187(2516), 12-13.

[5] Abaza A, Ross A, Ammar H. "Retrieving dental radiographs for post-mortem identification," In 2009 16th IEEE International Conference on Image Processing (ICIP), IEEE, 2009.

[6] Dayal PK. Textbook of forensic odontology. paras medical publisher; 1998.

[7] Kahana, T., & Hiss, J. (1999). Forensic radiology. The British Journal of Radiology, 72(854), 129-133.

[8] Clark DH. Practical forensic odontology. Butterworth-Heinemann, 1992.

[9] McGarvey, J. WinID: Dental identification system, 2005.

[10] Pretty, I. A., & Sweet, D. (2001). forensic dentistry: A look at forensic dentistry–Part 1: The role of teeth in the determination of human identity. British dental journal, 190(7), 359.

[11] Kenney, J., Standish, S., Souviron, R., Vale, G., Mcgivney, J., & Jones, G. (1994). Body identification guidelines. Journal of the American dental association, 125(9), 1244.

[12] Mahoor MH, Abdel-Mottaleb M, "Automatic classification of teeth in bitewing dental images." in 2004 International Conference on Image Processing, 2004.

[13] Chen, H., & Jain, A. K. (2005). Dental biometrics: Alignment and matching of dental radiographs. IEEE transactions on pattern analysis and machine intelligence, 27(8), 1319-1326.

[14] Hofer, M., & Marana, A. N., "Dental biometrics: human identification based on dental work information," in XX Brazilian Symposium on Computer Graphics and Image Processing (SIBGRAPI 2007), pp. 281-286. IEEE, 2007.

  Helix E-ISSN: 2319-5592; P-ISSN: 2277-3495

[15] Nomir, O., & Abdel-Mottaleb, M. (2008). Hierarchical contour matching for dental X-ray radiographs. Pattern Recognition, 41(1), 130-138.
[16] Nomir, O., & Abdel-Mottaleb, M. (2008). Fusion of matching algorithms for human identification using dental X-ray radiographs. IEEE Transactions on Information Forensics and Security, 3(2), 223-233.
[17] Lin PL, Lai YH, "An effective classification system for dental bitewing radiographs using entire tooth," in 2009 WRI Global Congress on Intelligent Systems, vol. 4, pp. 369-373. IEEE, 2009.
[18] Kuo CH, Lin PL, "An Effective Dental work extraction and matching method for Bitewing Radiographs," in 2010International Computer Symposium (ICS2010), pp. 495-499. IEEE, 2010.
[19] Harandi AA, Pourghassem H,"A semi automatic algorithm based on morphology features for measuring of root canal length," in 2011 IEEE 3rd International Conference on Communication Software and Networks, pp. 260-264. IEEE, 2011.
[20] Oktay, A. B. (2017). Human identification with dental panoramic radiographic images. IET Biometrics, 7(4), 349-355.
[21] Ajaz A, Kathirvelu D, "Dental biometrics: Computer aided human identification system using the dental panoramic radiographs," in 2013 International Conference on Communication and Signal Processing, pp. 717-721. IEEE, 2013.
[22] Joshi SV, Kanphade RD, "Forensic Approach of Human Identification Using Dual Cross Pattern of Hand Radiographs," in International Conference on Intelligent Systems Design and Applications, pp. 1075-1084. Springer, Cham, 2018.
[23] Ding, C., Choi, J., Tao, D., & Davis, L. S. (2015). Multi-directional multi-level dual-cross patterns for robust face recognition. IEEE transactions on pattern analysis and machine intelligence, 38(3), 518-531.

  Helix E-ISSN: 2319-5592; P-ISSN: 2277-3495