Human Identification Using Dental Biometrics- A Review

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Abstract- *Human identification is a vital component of forensic science, crime scenes, and in addition to mass disaster victim identification. There exists plenty of conventional biometrics such as fingerprint, face recognition, etc.; however, dental biometrics can be an excellent alternative as dental features are unique, non-easily wearable, and post-mortem resistant. This survey of the literature assesses some of the approaches used to identify a human being using dental biometrics, including the conventional approaches and the new methods used in image processing, machine learning, and deep neural networks. It examines the methodologies, highlights the substantive findings, evaluates the performance measures, and approaches the gaps present and probable subsequent studies on this topic.*

Keywords- Human Identification, Deep Learning, Dental Biometrics, Forensic Odontology, Image Processing, and Panoramic Dental X-rays.

I. INTRODUCTION

Precision of human identification is vital in forensic investigation particularly when other methods of identification are not used due to the compromises of the conventional methods caused by mass disasters or decomposition. The dental biometrics offer an attractive alternative where the unique features of teeth and the other oral structures have particular value since they are still relatively preserved even when the conditions might have resulted in extreme violence or when the time passed since death exceeded longer post-mortem times. The present paper gives an in-depth review of the literature dedicated to methodologies and results of the identification of humans based on dental biometrics. The purpose is to synthesize the existing literature, point out the methods of the analysis, outline the most important findings, and describe the future areas of research in this specialized area..

II. BACKGROUND ON DENTAL BIOMETRICS

Dental biometrics is based on the fact that the dentition of an individual is unique, and it contains such characteristics of the dentition as the type of the teeth, its size, its shape, position, and type of dental work (filling, crowns), as well as the peculiar structure of the mandible and maxilla bone. The given attributes develop early in the life of a person and are resistant to deterioration to a high degree, which is why they can be considered valuable forensic background. Dental radiographs and, in particular panoramic images of the X-rays are commonly used because they tend to give a unified panoramic picture of the all dentition and bone structures involved, which makes it possible to extract a range of biometric data. Although dental radiography forms a basis to a particular detailed profiling of the dental characteristics, alternatives are being examined by which the exposure to the radiations can be reduced or even avoided in order to use it in the context of identification [6].

III. LITERATURE REVIEW AND ANALYSIS

The body of literature on human identification, through dental biometrics, demonstrates a variety of feature extraction methods, either feature-based applied on image processing methods, or deep learning models.

A. Image Processing and Traditional Feature Extraction

Initial approaches on dental biometrics concerned dental X-rays and image processing to identify characteristics to be used to match the X-rays. Abdallah et al. [2] discussed the application of image processing as a method of improving dental X-rays by reducing noise as well as identifying teeth structures. In their work, the necessity of the pre-processing procedures to enhance the diagnostic and analytical worth of images is critical and is the key factor towards further identification processes. Following up on the feature extraction, a human identification system based on the extraction of mandibular data of panoramic radiography dental records was proposed by Banday and Mir [1]. They do that by dividing the mandible into sections to get the coordinates of the outer contour, based on which a time series is generated to capture structural data. Then a time series of such mandibles is fitted with an Autoregressive (AR) model and the estimated AR coefficients are used as a feature vector per mandible. The vectors are then utilized in matching and identification by means of Euclidean distance classification. They show experiments to determine the performance of the system at various models of the AR.

B. Dental Code Codification for Recognition

Besides morphological characteristics, there has been a look at the ideas of codifying the characteristics of teeth in order to recognize them sturdily. Muneeswaran et al. [3] also discussed the codification of the dental codes in a bid to identify the cogent recognition of an individual. Although how they go about codification of it is not explained, this method implies a systematic way of encoding more complicated aspects of teeth features (e.g. presence/absence of teeth, fillings, prosthetics) in a machine-readable state, which may allow efficient order matching and search speed in mass-scale applications. This procedure usually entails the conversion of visual dental records into a special numerical or alphanumerical code.

C. Deep Learning and Few-Shot Learning Approaches

With a revolution in artificial intelligence and the emergence of deep neural networks (DNNs), biometric recognition has changed significantly. Arag n Molina et al. [4] used deep neural networks to evaluate the legal age based on panoramic dental X-ray pictures. Their main idea is estimating age, though, the main premise behind the model is that DNNs have an ability to pick up rather complex and not-obvious characteristics when it comes to dental radiographs and apply it to the direct identification scenario. Capability of DNNs to accept raw data of an image and automatically identify patterns of interest lowers the dependence on manual feature-engineering. Another obstacle in the context of forensics is the lack of availability of ante-mortem records most of the time. The above problem was addressed by Ata&scedr increasingly educated to existing approaches to biometric identification based on panoramic dental radiographic images and few-shot learning by Ata&scredil cents et al. [5]. Such paradigm allows models to generalise and carry out identifications very well even in having a very small number of training examples thus is very applicable in real life situation in forensic investigation due to the scarcity of completeness of databases. Moreover, Dela Cruz et al. [6] designed an entire identification system in which there are intents of avoiding harmful radiation. They used a Recurrent Neural Network (RNN) in their system to deliver classification of feature vectors taken out of the photos obtained by a USB camera. They used several techniques of processing these images (Image Stitching with OpenCV, Contrast Limited Adaptive Histogram Equalisation, and Adaptive Harris Corner Detection Algorithm) to analyse them. This is the multidisciplinary presentation of the fusion of image acquisition, enhancement, traditional features and the modern neural networks.

D. 3D Dental Biometrics and Advanced Architectures

The replacement of 2D radiographs with 3D imaging provides a better and detailed explanation of the dental structures avoiding the problem of projection distortion. Fu and Damer [7] presented another general survey of biometrics recognition in the 3D medical images such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT). They improve 3D security and biometric data(dmms archive). They cannot be called wholly dental yet their work draws attention to the fact that 3D data provides more detail to and is richer in information content that biometric security to identify patients (medical environment). In particular, as a means to apply to dental applications, Zhang and Zhong presented a 3D extraction and matching of dental arch based on a transformer [8]. Transformers, which have been originally designed with natural language processing, have demonstrated superior performance in the domain of computer vision in the detection of long range dependencies as well as complicated spatial configurations. The implementation of this architecture on 3D dental data leads to a high zip-discriminative feature extraction on the whole arch of dental data and this is a major contribution in robust 3D dental biometric systems.

IV. RESULTS AND DISCUSSION

As evidence in the literature reviewed, there is an evident evolution of dental biometrics in providing human identification: from manual and semi-automated to automated and smarter systems.

A. Comparative Analysis of Methods

Table I will present a comparative overview of the methodologies, nature of data and the main contribution of the reviewed literature. It must be said that certain measurable performance indicators (e.g., accuracy, FMR, FNMR, EER) were usually not presented in the presented excerpts of the original articles, therefore restricting a direct numeric comparison in the scope of this survey. The table highlights the conceptual, as well as the methodological contribution.

TABLE I. COMPARATIVE OVERVIEW OF DENTAL BIOMETRIC IDENTIFICATION METHODS

Reference	Primary Focus/Goal	Key Methodology	Data Type/Characteristics	Key Contribution/Note
[1] Banday & Mir	Human identification via mandibular features	Mandible segmentation, AR model fitting to contour time series, Euclidean distance classification	Panoramic dental X-rays (120 ante-mortem, 90 post-mortem)	System for human identification using structural information of the mandible.
[2] Abdallah *et al.*	Enhancement of dental X-rays	Image processing (denoising, dental structure detection)	Dental X-rays (OPG)	Emphasises the importance of pre-processing for improved diagnostic and analytical value.
[3] Muneeswaran *et al.*	Codification of dental codes for recognition	Codification of dental characteristics (specifics not detailed)	Not specified (implies structured dental records)	Aims for a structured, machine-readable representation of dental features for efficient matching.
[4] Aragón Molina *et al.*	Assessing legal age from dental X-rays	Deep Neural Networks (DNNs)	Panoramic dental X-ray images	Demonstrates DNN capability to extract complex features from dental radiographs; potential for identification.
[5] Ataş *et al.*	Biometric identification with limited data	Few-shot learning, panoramic dental radiographic images	Panoramic dental radiographs	Addresses the challenge of limited ante-mortem records, enabling generalisation from small examples.
[6] Dela Cruz *et al.*	Radiation-free human identification system	USB camera image acquisition, Image Stitching, CLAHE, Adaptive Harris Corner Detection, Recurrent Neural Network (RNN)	Optical images of teeth (captured by a USB camera)	Develops a complete, non-radiation identification system using integrated techniques.
[7] Fu & Damer	Survey on 3D medical image biometrics	Survey of 3D imaging (MRI, CT) and biometric applications	3D medical images (general, includes dental)	Highlights the benefits of 3D data for biometric security and patient identification; notes data scarcity.

[8] Zhang & Zhong	3D dental arch extraction and matching	Transformer-based approach	3D dental models	Advances in 3D dental biometrics using sophisticated deep learning architecture (transformers).

TABLE II. IDENTIFICATION PERFORMANCE METRICS

Reference	Metric Type	Value(s)	Notes/Context
[1] Banday & Mir	Recognition Rate (RR)	75.52%	At AR model order 3.
	Equal Error Rate (EER)	23%	For identification.
	Rank-1 Identification Rate	76.66%	For identification.
[4] Aragón Molina *et al.*	Classification Accuracy	84.1%	For legal age assessment (binary classification: ≥18 vs. <18 years).
[5] Ataş *et al.*	Rank-1 Accuracy	84.72%	Achieved using Cosine and Pearson similarity metrics.
	Rank-10 Accuracy	97.91%	For identification.
[6] Dela Cruz *et al.*	Computed Reliability (Accuracy)	83.33%	For overall identification system based on matched/mismatched data.
[8] Zhang & Zhong	Top 6.5% Accuracy (Rank-13/200)	100% (for 11 samples)	Meaning all 11 PM samples were found within the top 13 ranks out of 200 AM samples.
	Identification Time	3 minutes/subject	Reduced from 5 minutes (previous work).

B. Identification Performance Metrics

Table II summarises the quantifiable performance metrics reported by the surveyed papers directly relevant to human identification or age assessment from dental data. It is important to note that direct comparisons between these metrics can be challenging due to differences in datasets, evaluation protocols, and the specific tasks addressed by each study (e.g., identification vs. age assessment).

C. Overall Accuracy and Reliability

The past practices that incorporate both the image processing and statistical models (e.g., AR models of mandibular contours [1]) have shown the underlying accuracy that often depends on strict extraction of geometric and morphological characteristics. With deep learning, where articles are concentrated on age estimation [4] and direct identification [5], [6], there is demonstrated a large improvement in the possibility of success, by automatically learning complex feature representations that may be complicated to reflect human-designed algorithms. The few-shot learning algorithms show a lot of potential when it comes to real-life cases where the ante-mortem data is not abundant [5].

D. Technological Advancements

The move towards 3D imaging (CT, MRI) and the use of more sophisticated deep learning architecture such as transformers [8] are increasing not only the fidelity and plenitude of data available to identification but also ease many of the ambiguities posed by 2D projections.

E. Automation and Efficiency

The tendency to automate processes, including the incorporation of image enhancement [2], features extraction and classification [6], is to produce less processing time and human error, to enable the more efficient and scalable process of identification, including mass destruction situations. The codification of the dental information [3] also contributes to the establishment of structure databases that can be searched in short mode.

F. Challenges

In spite of all these developments, there are a number of problems that remain. The insufficiency of big, open, and differing datasets is an enormous obstacle to the training of sturdy deep learning models [7]. System performance can be affected by variations in image protocols of acquisition image quality, dental pathology and degree of post-mortem changes. Moreover, the interpretability of certain deep learning models may be hindered by the so-called benefit of the black box: Since certain deep learning models have a black-box character to some extent, they cannot be understood as easily or evenly as it is necessary to validate them forensically and allow them to be accepted in a court of law[9].

V. GAPS IN THE LITERATURE AND FUTURE RESEARCH DIRECTIONS

- At the level of existing research, there are several gaps and possible future directions that may be singled out:
- **Standardised Benchmarking Datasets:**Ethically-acquired, wide-scale, diverse public 2D and 3D datasets of dental data (both ante-mortem and post-mortem) of multiple populations, ages, and conditions provide the most critical necessary item. These data are paramount in serious benchmarking and evaluation of various algorithms.
- **Resistance to Real-World Pitfalls**: Future work needs to concentrate to devise algorithms that are resistant to typical real-world realities, including noise, artefacts, incomplete dental records, heavy dental work (e.g. orthodontics, prosthetics), and varying levels of post-mortem decay.
- **Multi-Modality Data Fusion**: Fusion of data regarding various features of the teeth (e.g. morphology, root structure, dental work, shape of the mandible), and possibly other biometrics (e.g. face structure using CT scans) may result in more reliable and accurate identification systems. There should be research on the best strategies of fusing multi-modal dental data.
- **Explainable AI (XAI) that can be validated in forensics:** Deep learning models have been shown to perform well, but are criticized because they are black-boxes, making them a liability in legal admissibility. Future research ought to look into how it uses XAI to make such models less opaque, and XAI should leave forensic experts with a sense of why a specific identification was obtained to provide more trust and acceptance.
- **Longitudinal Research on Dental Feature Stability:** There is a need to undertake more research and see how dental biometric features evolve during the life of an individual. Age-invariant identification algorithms could be informed by longitudinal data.
- **Non-Invasive 3D Imaging:** The field of research that focuses on developing non-radiation-based 3D methods of dental imaging that can be applicable in a forensic setting may yield a broad amount of information, without the relative health risks or ethical issues attached to use of radiation imaging [6].
- **Secure and Interoperable Dental Biometric Systems:**With the expected increase in such systems, studies concerning the security of data storage and retrieval and the interoperability of the various forensic agencies and dental databases will prove very important[10].

VI. CONCLUSION

Dental biometrics has become an exclusive and very robust method of human identity, which in the case of forensics, is extremely useful where conventional methods fail. The sphere has undergone a tremendous change, the once tedious and time-consuming work of manual analysis and image processing procedures to advanced deep learning-based architecture that is able to process complex 2D and 3D files of dental models. The potential of these inventions is enormous as far as more accurate, automated, and efficient identification processes are concerned. Nevertheless, the creation of standardised databases, subsequent testing under the harsh real-life conditions, and the construction of more human-interpretable AI models are the key next steps towards the diffuse and unhesitant use of dental biometrics in identifying humans. Dental evidencefinds a secure future in forensics due to its sheer individuality and persistence.

REFERENCES

[1] M. Banday and A. H. Mir, Dental Biometric Identification System using AR Model, International Journal of Pattern Recognition and Image Analysis, vol. 8, no. 4, pp.537-559, 2017.

[2] Y. M. Y. Abdallah, N. H. Abuhadi and M. H. Mugri, Enhancement of Dental X-rays images using Image Processing Techniques, Journal of Research in Medical and Dental Science, vol. 9, no. 2, 2021, 12-16.

[3] V. Muneeswaran, M. Vasundhara, P. Nagaraj and G. Kalyan, Codification of Dental Codes for the Cogent Recognition of an Individual, in Proc. 2021 5th Int. Conf. Intelligent Computing and Control Systems (ICICCS), May 2021, pp. 141146.

[4] A. J. Arag n Molina, D. De Angelis, F. Scotti, R. D. Labati, and V. Piuri, Deep Neural Networks to assess the legal age using panoramic dental X-ray images, in Proc. 2024 IEEE, 2024, pp. 18.M. Ata(ggounova voter, C. Ozdemir, Ismail, 2009).

[5] Ata, B. S n-Ak and E. Ozero, l Biometric identification on panoramic dental radiographic images with few-shot learning, Turk. J. Elec. Eng. & Comp. Sci., vol:30, issue:3, pp: 1115-1126, April 2022.

[6] J. C. Dela Cruz, R. G. Garcia, J. C. C. V. Cueto, S. C. Pante and C. G. V. Toral, Automated Human Identification through Dental Image Enhancement and Analysis, Int. J. Eng. Technol. Manage. Appl. Sci., 8/11, 41-48, 2020.

[7] B. Fu and N. Damer, Biometric Recognition in 3D Medical Images: A Survey, IEEE Access 11 no. 11, (Nov. 2023), 125615-125642.

[8] Z. Zhang, X. Zhong, 3D Dental Biometrics: Transformer-based Dental Arch Extraction and Matching, in Proc. 2023 IEEE Conf. Artificial Intelligence (CAI), Santa Clara, CA, USA, Jun. 2023, pp. 139 140.

[9] Nirmala S Guptha, Kiran Kumari Patil,"Earth Movers Distance Based CBIR Using Adaptive RegularizedKernelFuzzyCMeansMethodOfLiverCirrhosis Histopathological Segmentation",InternationalJournalofSignal and Imaging Systems Engineering, Inderscience Publishers, Vol.10, Nos.1/2 2017, (IJSISE; e-ISSN:1748-0701,p-ISSN:1748-0698),pp39-46DOI:[http://dx.doi.org/10.1504/IJSISE.2017.10005432,](http://dx.doi.org/10.1504/IJSISE.2017.10005432)IF-1.09,

[10] Kamalalochana,N.S.,Guptha,"Optimizingrandomforesttodetectdiseaseinappleleaf",InternationalJournalofEngineeringand AdvancedTechnology, 2019,8(5SpecialIssue),pp.244–249.