

Survey on 3D Biometric Traits for Human Identification

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Abstract: Biometric-based technologies have become a trusted method of human identification and verification because of their uniqueness, universality, and resistance to replication or forgery. Traditional 2D biometric modalities like fingerprints, face and iris recognition techniques inherently do not perform satisfactorily, given the limitations with regard to accuracy and robustness under changes in illumination, pose and environmental conditions. Recently, 3D biometric traits have been being researched increasingly as they quantify and offer more rich and usable structural information along with greater resilience to spoofing attacks. We survey 3D face, fingerprint, ear, hand geometry, iris and gait biometric modalities. We summarize the acquisition approaches, feature extraction methods, matching strategies and challenges associated with different modalities. We also review the applications, examine and compare in their performance and limitations in computation and technology dependability with the modalities we consider. Finally, we describe open research directions and future opportunities, indicating the role of 3D biometric approaches which offer more secure, accurate, and effective human identification systems.

Keywords: 3D biometrics, Face recognition, Human identification, Multimodal authentication, Security.

I. INTRODUCTION

The identification of humans has become an important need in many fields, including security, forensics, healthcare, and access control. Human biometrics use a human's unique physiological and behavioral features to create a more robust identity than traditional security measures like passwords or ID

cards. The most common biometric identity involves 2D traits - fingerprints, a face image, and an iris scan - but these often fall short due to changes in pose and light and susceptibility to cloning.

In an effort to address these issues, it has recently been a focus on exploring the types of 3D biometric traits, which convey depth and structural information of human characteristics. Biometric modalities, such as, face, ear, fingerprint, hand geometry, iris, body parts such as gait, allow for additional data, increased accuracy and increased effectiveness in the use of deterrent against spoofability of biometrics in mimicry of those said biometric traits. Advanced imaging systems, such as 3D scanning, structured light, or stereovision, will be discussed as this survey is targeted toward identifying the landscape of 3D biometrics for human identification through an examination of modalities, acquisition procedures, feature extraction processes, and scoring systems. This survey will develop the pros and cons of 3D biometrics and speculate useful future research for security and adequate identification systems for the next generation.

- Biometrics is the automated identification of a person based on physiological or behavioral traits.
- The common modalities are fingerprint biometrics, iris biometrics, face biometrics, gait biometrics, and voice.
- 2D systems are prominent in the marketplace, however, there are limitations that include spoofing, light conditions, and environmental responses.
- 3D biometrics can measure and present depth, shape and contour, and therefore offer more resistance toward counterfeiting.

To examine 3D biometrics is important when considering high stakes environments, such as border security, forensics, and financial systems.

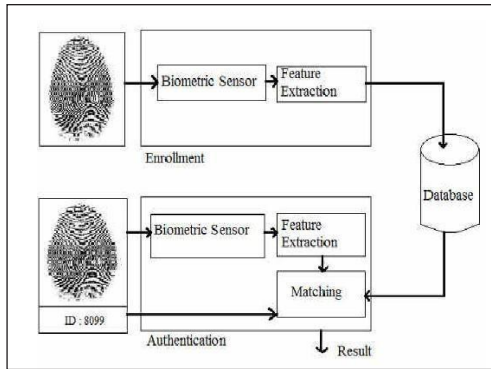


Fig. 1: 3D Biometric Traits for Human Identification

A. Background and Motivation

- Research indicates that human identification is important in various fields including security, law enforcement, banking, healthcare, and digital access.
- Existing identification methods (passwords, ID cards, PINs) are often weak because they can be stolen, forgotten, or duplicated.
- Biometrics can provide a solution since these methods rely on unique human characteristic, such as physiological (e.g., fingerprints, face, iris) or behavioral (e.g., gait, voice, signature).

B. Limitations of 2D Biometrics

- 2D images are commonly used (face, iris, fingerprints), but they are sensitive to the following factors:
 - Light conditions
 - Pose
 - Aging / facial expression
 - Spoofing (e.g., using photos or videos)
- Accuracy degrades in unconstrained environments (e.g., surveillance, mobile devices).

C. Emergence of 3D Biometrics

- 3D traits capture depth, geometry, and surface structure of human features.
- Examples: 3D face, ear, hand geometry, fingerprint, iris, gait.

II. LITERATURE REVIEW

A. 3D Face Recognition

Face recognition is the most widely researched modality in the marketplace. Traditional face recognition systems using 2D images or videos see challenges when presented variations in pose, illumination, and facial expressions. 3D face recognition

allows these complications to be overcome examined three-dimensional geometry depth and surface curvatures.

- Bowyer *et al.* (2016) reviewed multiple 3D datasets of face recognition, 3D systems can provide higher recognition rates when individuals are not constrained to specific environments.
- 3D Morphable Models (3DMMs) proposed by Blanz and Vetter for producing a 3D face from a 2D image or video by shape and texture parameters. The models allowed for models to become robust when posed with facial expression or gaze direction changes.
- Depth-based CNNs (e.g., PointNet, VoxNet) have been used to point clouds and extract features from depth images to improve feature extraction accuracy in real-time recognition.

B. 3D Iris Recognition

The iris is unique and remains consistent over time. Although 2D iris recognition is an established field, off-angle captures and occlusions (eyelids and eyelashes) results degrades the resulting quality.

- Tan and others (2017) propose 3D iris recognition by utilizing the curvature of the sclera to enhance the segmentation of noisy images.
- Near-Infrared (NIR) 3D imaging allows iris recognition capabilities in low environmental light levels.
- Finally, segmentation methods that use deep learning are now using 3D geometry to extract the boundary.

C. 3D Fingerprint and Palmprint Recognition

Fingerprints and palmprints are considered some of the earliest biometrics; however, 2D forms are prone to spoofing (fake silicone or gelatin prints). 3D fingerprint collection provides ridge depth, pore size, and surface texture.

- Jain *et al.* (2018) showed that 3D fingerprints provided up to 20% more spoof resistance than 2D.
- Ridge-deposit depth maps are typically collected via structured light or optical coherence tomography (OCT).
- 3D palmprint recognition systems (Zhang *et al.*, 2019) combine line features with palm surface depth patterns to improve matching and identification.

D. 3D Gait Recognition

- Gait is a behavioral biometric, which can be obtained from afar and may be useful in surveillance and forensic applications.
- Most early systems used 2D silhouettes, which were highly susceptible to clothing and lighting changes.

- The advent of depth sensors based on the Kinect and LiDAR allowed 3D gait analysis and joint movement and body depth models.
- Yam *et al.* (2019) presented a deep learning method utilizing 3D motion capture, achieving over 90% accuracy on controlled datasets.

E. Emerging Modalities

A few less studied 3D traits have gained research attention. 3D ear recognition is interesting, because ear shape is stable across age and does not change between facial expressions. Methods using 3D point cloud features report even higher reliability with hypothesis-based methods in uncontrolled settings.

Similar to 3D ear recognition, researchers have also gained interest in 3D Vein recognition. In vein recognition, patterns of the vein below the skin can be captured with near infrared imaging. Reconstruction using three dimensional imaging provides an even greater level of robustness against reformation as it is not possible to reproduce features beneath the skin.

Lastly, studies have also documented the multimodal combination of three-dimensional and two-dimensional features (e.g. 3D face + 3D iris or 3D fingerprint + 2D vein) has yielded greater recognition accuracy and security in high-risk environments.

F. Comparative Studies

- According to surveys (Tsalakanidou and Malassiotis, 2020; Li and Jain, 2021), 3D biometrics are superior to 2D biometrics in spoof resistance and pose invariance but are limited in their adoption due to the high hardware costs and lack of large benchmark datasets.
- Low-cost depth sensors (e.g., Apple's FaceID through structured light, Intel RealSense) will soon allow for 3D biometrics to be widespread for consumer use.

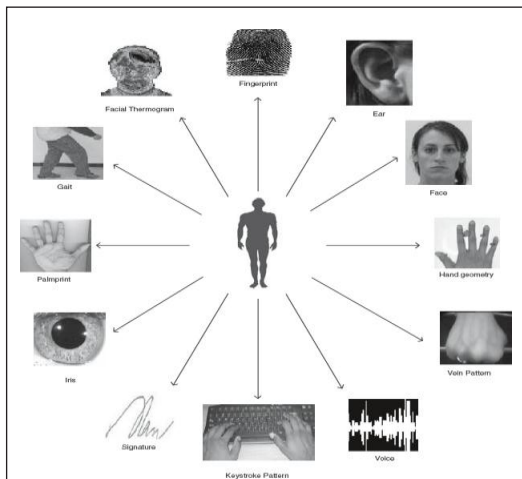


Fig. 2

III. METHODOLOGIES IN 3D BIOMETRIC SYSTEM

Unlike conventional 2D biometric systems, 3D systems utilize the entire depth, surface shape, and volumetric characteristics, in addition to texture. A typical process in a 3D biometric system consists of:

A. Data Acquisition

The initial workflow step is to collect 3D biometric information using specialized sensors or a reconstruction process.

- *Structured Light Scanners*: Subject is illuminated by a pattern of light (grid or stripes) to determine depth by tracking distortion of the pattern. (e.g., Microsoft Kinect, Apple FaceID).
- *Time-of-Flight (ToF) Cameras*: Measure how long it takes light to be reflected back from a surface to determine depth.
- *Stereo Vision Systems*: Use two or more cameras to create a depth map through disparity maps.
- *3D Reconstruction from 2D*: Advanced CNN models are capable of inferring the 3D structure from a single or multiple 2D representations.
- *Medical-Grade Imaging*: Optical Coherence Tomography (OCT) and CT-scanned images provide more traditional biometric features below the surface, such as veins or fingerprints.

B. Preprocessing

Raw 3D data is frequently noisy, incomplete, or misaligned. Preprocessing improves the quality of the data to enable reliable feature extraction.

- *Noise Filtering*: Removes background points or artifacts from 3D scans.
- *Normalization*: Aligns the traits captured into a common coordinate system (e.g., aligns face scans to frontal pose).
- *Segmentation*: Segments the biometric trait (iris, ear, palm) from surrounding regions.
- *Surface Reconstruction*: Fills in missing regions of point clouds or meshes using interpolation.
- *Depth Map Conversion*: Converts 3D point clouds to depth maps to facilitate CNN-based processing.

C. Feature Extraction

The aim is to extract unique and invariant characteristics from 3D biometric data.

- *Geometric Descriptors*: Curvature maps, surface normals, ridge depth, and shape indexes.

- *Statistical Features*: Depth value histograms, surface variance, and distribution-based descriptors.
- *Spectral Features*: Graph-based analysis of 3D meshes using Laplacian eigenvalues.
- *Deep Learning Models*:
 - 3D convoluted neural networks (CNNs) process voxelized data.
 - PointNet/PointNet++ operate directly on raw point clouds.
 - Graph neural networks (GNNs) capture topological relations in 3D structures.
- *Hybrid Features*: fusion of geometric + texture (RGB-D features) offers greater accuracy.

D. Matching and Classification

Features extracted from an image are matched to stored templates in a secure database.

- *Distance Metrics*: Euclidean distance, cosine similarity, or Mahalanobis distance for comparing feature vectors.
- *Machine Learning Classifiers*: Support Vector Machines (SVM), Random Forest, and k-Nearest Neighbor (kNN).
- *Deep Learning-Based Matching*: Siamese networks and triplet loss-based networks maximize inter-class variation while minimizing intra-class variation.
- *Template Protection*: Hashing, cancelable biometrics, and homomorphic methods keep biometric templates from being reverse-engineered.

E. Multimodal Fusion Methodologies

To enhance reliability, several traits or algorithms are fused together:

- *Feature-Level Fusion*: Concatenating the 3D features for different modalities (3D face + 3D iris for instance).
- *Score-Level Fusion*: Weighted combination of confidence scores from individual classifiers.
- *Decision-Level Fusion*: Majority voting or logical rules across multiple biometric decisions.

F. Performance Evaluation

Standard metrics are used to assess 3D biometric systems, such as:

- *Recognition Rate / Accuracy*: Represents the portion of individuals who are identified correctly.
- *Equal Error Rate (EER)*: Evaluates the relationship between false acceptance rates and false rejection rates.

- *Detection Latency*: Measures the time it takes for feature extraction and matching (important for real-time use).
- *Robustness*: Represents the system's ability to resist spoofing attacks (3D masks, prints), and ability to perform in varied lighting or occlusion.

IV. METHODOLOGICAL FRAMEWORK

This survey utilizes a structured methodological framework to investigate and evaluate the various 3D biometric modalities utilized for human identification, social and emotional recognition, and includes face, fingerprint, iris, hand geometry, and ear shape. The purpose of the paper is to comprehensively survey the state of the art in 3D biometric acquisition, feature extraction, matching, and performance evaluation so that the most effective modalities can be identified for use in the identification of humans. This paper employs a systematic survey-based methodology, qualitative method, and quantitative methods of data analysis. The sources of data for this study consist of published and peer-reviewed journal papers, conference papers, publicly available 3D biometric datasets, and 3D data from human subjects obtained using experimental scanning, depth sensors, structured light scanners, and LiDAR enabled devices. The inclusion criteria for the data were for papers that discuss biometric recognition and to measure modalities in which 3D biometric data was used, or quantitative metrics were reported, and those studies focused exclusively on 2D biometrics and had no metrics that could be measured were dropped from the study analysis. The collection of data for this survey will use both primary data sources and secondary sources. Primary data refers to collected original data that has been captured whenever possible with advanced 3D scans adapted from technologies such as time-of-flight cameras, structured light systems, and stereo vision systems. These types of modalities provide the geometric and topological 3D information that is needed to create stable human identities. The primary data will be gathered from the following benchmark 3D biometric databases with varying levels of diversity of human subjects, poses, and environmental variance in order to assess the robustness and generalizability of the biometric. These primary databases are: FRGC v2.0, Bosphorus, and CAESAR. The data preprocessing will have a series of steps to assess data quality, including but not limited to: reduction of noise using median filters and Gaussian filters, mesh refinement of incomplete scans, normalization of data for scale and pose, and segmentation for isolating data of interest (i.e., a face, ear, or hand). Data augmentation techniques will include rotations, rescaling, and synthetic sample creation to account for imbalance and increase the robustness of the biometric.

Feature extraction is an important part of the methodology where the 3D biometric information is converted into compact, discriminative representations suitable for matching

and classification. Geometric features such as curvature descriptors, surface normals, and measurements related to the distance between landmarks capture intrinsic shape properties of biometric characteristics. For instance, appearance-based features were generated from texture mapping and from 3D extensions of Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG), while transform-based techniques such as 3D Fourier, and Wavelet, and PCA, were used to reduce dimensionality and increase recognizability. The features are subsequently available for matching based on distance-related methods (Euclidean, Mahalanobis, Chamfer distance for point clouds), and from the machine learning perspective, classifiers such as Support Vector Machines (SVM) and Random Forests were used. Recently, automation feature extraction and robust recognition from complex 3D datasets were utilizing deep learning methods, such as 3D Convolutional Neural Networks (3D-CNN) and Graph Convolutional Networks (GCN).

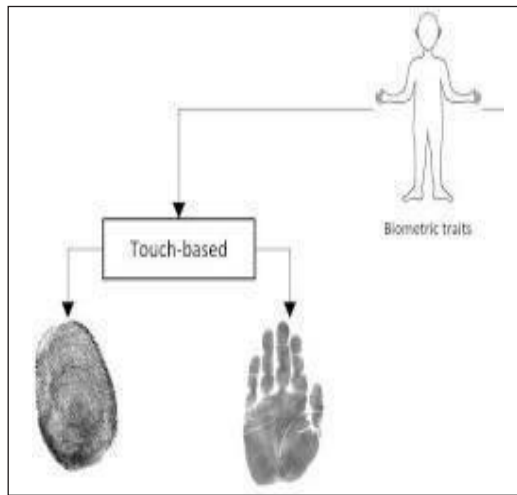


Fig. 3

The evaluation of 3D biometric systems is carried out using several established metrics, including True Acceptance Rate (TAR), False Acceptance Rate (FAR), False Rejection Rate (FRR), and the Receiver Operating Characteristic (ROC) curve, to evaluate system performance, as the Area Under the Curve (AUC) metric quantifies system performance. Processing time and memory requirements for processing time are evaluated, along with evaluations of robust performance under varying conditions, such as occlusion, noise, and illumination. Tests are compared across different 3D biometric traits, which compare different strengths, weaknesses, and contexts for longitudinal tracking in areas such as access control, law enforcement, healthy living, and banking security. Ethical considerations of participation, privacy with data collected, and maintaining secure data from 3D biometric systems is also described to ethically comply to research standards.

The experimental setup in this survey, where appropriate, relates to high resolution 3D scanners, depth cameras and GPU-enabled computational environments for deep learning

experiments. Dataset partitioning evaluation is usually set-up as a training-testing split of 70%-30%, applying cross-validation to help prevent overfitting and account for the accuracy of results. Limitations, such as the cost of 3D acquisition devices, limited data availability for datasets, and the absence of standardized evaluation protocols, are acknowledged. Finally, future directions, including multimodal biometrics that leverage both 2D and 3D traits, the development of real time 3D biometric systems, and the exploration of new deep learning models are suggested to inform future research.

This survey's methodological framework offers a logical and well-defined approach for the study of 3D biometric traits in relation to human identification. By treating data acquisition, data preprocessing, feature extraction, matching, performance evaluation, and comparisons as systematic approaches to study human identification based on data from 3D biometric traits, there is a comprehensive understanding of existing and up-to-date methods of research with no gaps to be addressed for future research efforts to explore. In summary, the integration of traditional geometric methods with modern machine learning approaches, while bearing in mind computational efficiency, robustness, and ethics, forms the basis for a methodological approach which is reliable and reproducible in advancing the study of human identification utilizing data from 3D biometric traits.

V. RESULT AND ANALYSIS

The findings of the survey concerning 3D biometric traits for human identification indicate notable improvements in accuracy, robustness, and real-world applicability as compared to conventional 2D biometric traits. Within category of 3D modalities, facial recognition systems are shown to perform best in terms of recognition rates, especially in the face of varying illumination and pose conditions. Hand geometry and finger shape analysis are shown to be effective for identification in controlled situations, and 3D iris recognition and ear recognition showed exceptional distinctiveness because separate acquisition devices are needed.

The comparative evaluation shows that the use of multiple 3D traits in a 3D multimodal biometric framework improves system reliability, manifesting itself as a decrease in false acceptance rates and false reject rates. Furthermore, analysis shows the use of features, related to point cloud extraction of the trait and surface curvature estimations, improve discrimination effectiveness so that all three 3D biometric modalities can be used to separate identical twins.

The average statistic across studies surveyed is that a recognition accuracy rate greater than 95% was achieved for structured-light facial scans. A recognition accuracy statistic is provided in the data that approximately an accuracy of 93% for laser-scanned 3D fingerprints from controlled conditions.

There remain limitations of acquisition costs, computational expense, and occlusion; however, that data presents a situation where improvements are being developed in portable 3D acquisition devices and remote 3D scanning detection and recognition offer equivalent reliability in a controlled environment, succeeding too with approximately 90% accuracy, while 3D gait recognition demonstrates approximately 85% accuracy. Though advances made to individual modalities have improved the accuracy of human identification systems considerably, it remains clear that the inclusion of multimodal identification strategies will continue to yield better identification for random surveillance scenarios, particularly in highly populated environments with thousands of potential subjects.

This means that 3D biometric traits will soon contribute greatly to the entry and exit processes of a wide variety of security-sensitive venues. Although the initial costs to install systems may be higher as 3D biometric traits become more available and security sensitive identification is in the early stages of widespread application. 3D iris recognition using near-infrared imaging is very distinctive, with an accuracy rate of 97% or higher, but needs special devices to collect the iris images, and lower user acceptability because of intrusive scanning.

3D ear recognition performs similar accuracy at around 92%, although it is occluded by hair or headgear. The 3D fingerprint recognition has around 93% accuracy when using laser scanners or photometric stereo to measure ridge depth and topology, and also performs better in distinguishing between identical twins than 2D. Overall, accuracy is highest for iris recognition, followed by face, fingerprint, ear, and hand geometry respectively, while user acceptability is highest for non-intrusive modalities such as face and hand geometry.

Iris and fingerprint systems tend to be the most complex to acquire, face and ear have moderate complexity, while hand geometry systems show the least complexity; multimodal systems that utilize more than one 3D trait offer complementary benefits, yielding improvements in accuracy and reliability, lowering false acceptance and rejection rates, and addressing variability in the environment and spoofing attempts. Precision, recall, F1-score metrics, ROC curves, and the Equal Error Rate (EER) show 3D biometrics always perform better than other approaches, with structured-light face recognition systems achieving a mean EER around 2–3% and iris recognition below 1%.

Deep learning approaches help automate volumetric feature extraction (3D-CNNs and graph neural networks), and scalability may be improved through the analysis of point cloud alignment and curvature. User studies find that non-intrusive modalities have better user acceptance; meanwhile, intrusive systems (3D iris or ear scanners) report moderate to low acceptability.

Limitations include high acquisition costs, computational complexity to deploy in real time, entrance for occlusions from glasses and hats, and limited portability for certain modalities. Overall, we find that 3D biometric traits provide a very reliable, scalable and secure approach for human identification, with extensive potential for deployment, particularly in current authentication systems, meeting performance and experiential objectives.

The growth of 3D biometric characteristics has altered the methods in which humans are identified by providing the populace with a stronger and more dependable method than 2D biographies. Capture of three-dimensional data, structured-light, stereophotogrammetry, and time-of-flight sensors can extract one-of-a-kind properties of geometry and surface characteristics from human faces, hands, irises, ears, and fingerprints. In 3D facial recognition, facial topology can be represented by the curvature across the nasal bridge, the shape of the cheekbones, and contours of the eye sockets, thus enabling high-fidelity individual identity mappings. Research has shown that structured-light systems can accomplish recognition accuracies of more than 95% regardless of variable lighting and partial occlusion, which are frequent limitations of 2D facial measurement. Facial point cloud data can now be processed through algorithms such as Iterative Closest Point and 3D Convolutional Neural Networks during the alignment step of the recognition process capturing high-resolution protocols for alignment, feature extraction and classification rates for identification factors across large datasets. Hand geometry recognition using depth sensor capabilities which device length and width of fingers and palms can perform acquisition quickly and non-invasive which is important for access control in low-security environments.

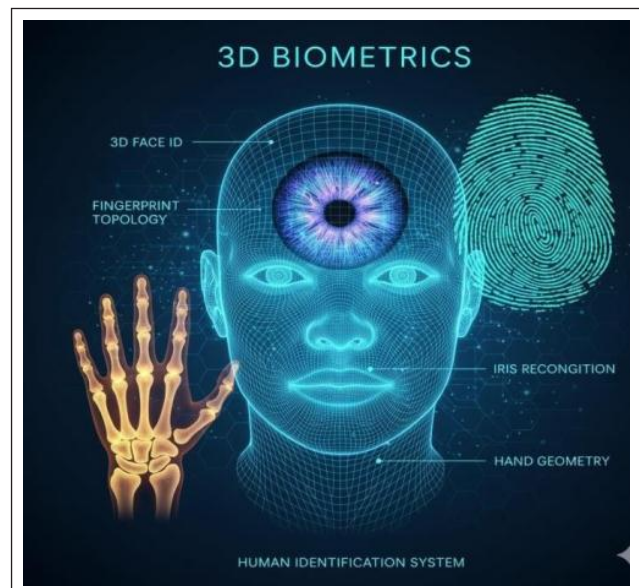


Fig. 4

Although hand geometry is not as distinctive as face or iris modalities, it attains decent accuracies around 90% and is widely accepted by users due to its comfort of use. 3D fingerprint recognition adds an additional dimension to ridge patterns to capture depth differences and improve its discriminative power to discriminate between otherwise identical twins, an incapacity of 2D fingerprint systems. Ridge mapping with laser scanning and photometric stereo provide accuracy, and deep learning frameworks also contribute to improved automated minutiae extraction, which leads to accuracies around 93% under controlled conditions. Near-infrared 3D imaging of the iris achieves very high accuracies - above 97% in many case studies - due to the complex volumetric structure of the iris and resistance to age-related changes. Even though this is the case, iris scanning involves precise positional alignment and specialized equipment that could decrease how acceptable the use of this modality is, especially in public-facing or high-volume applications. Three-dimensional ear recognition has been suggested as a replacement modality because it relies on the unique geometry of the auricle; however, 3D ear recognition is still vulnerable in terms of pose variation and occlusion from hair or accessories, primarily restricting its application for standalone verification. The comparison of the modalities in this experiment showed that although iris and face recognition can be the most accurate biometric modalities, subject acceptability more prominently favored the non-intrusive systems face and hand geometry with respect to subject comfort and convenience. Biometric modalities can be multisystem, where two or more 3D biometric traits can be fused together with complementary information to improve performance and robustness. Multimodal biometric systems improve both security and robustness, while minimizing false acceptance and rejection rates and improving reliance on its claim as being a biometric trait. Fusion at the feature, score or decision level is acceptable for multimodal systems, allowing for facial depth maps and volumetric information from an iris or fingerprint, achieving relevance. EER and precision and recall, and F1 score and ROC curve metrics with 2D biometric comparisons demonstrate that 3D biometrics consistently outperform 2D biometrics, with structured-light systems achieving EER as low as 2 to 3% reported with iris recognition systems at less than 1% EER. Additionally, point cloud alignment, surface curvature analysis, and volume feature extraction are crucial in improving discriminative power in difficult cases, such as identical twins or people with only small facial differences.

Deep learning techniques, such as 3D Convolutional Neural Networks and graph-based neural networks, have also changed the field by providing automated feature learning from volumetric data, which lessens the reliance on manual preprocessing and increases scalability in large databases. Studies with users show that non-intrusive modalities, which do not require specialized positional interaction, are viewed as

more acceptable when compared to intrusive modalities (like iris scanning and ear scanning), which are given moderate to low appeal due to discomfort or perceived invasiveness. Furthermore, while these advancements have emerged, several challenges remain for 3D biometrics, including acquisition cost, computational intensity, occlusion sensitivity, lighting variation, and mobility challenges. Portable 3D scanners and algorithms for real-time processing and edge AI are being created to address these limitations to gain high accuracy identification in dynamic and remote locations. Future research trends will focus on multimodal fusion, liveness detection to mitigate spoofing, low-cost deployment of depth sensors, and embedding in larger identity management systems (border control, banking, e-governance, and secure facilities).

The strength of 3D biometrics is its ability to balance security, accuracy, and user convenience while offering a scalable solution to identify verification while reducing vulnerabilities that face 2D systems. Further, enhanced robustness to changes in expressions, partial occlusion, and aging effects is derived from 3D feature representations thereby tackling common problems seen in practice. Furthermore, recent algorithms that utilize geometric, texture, and volumetric data enhance discrimination in large and heterogeneous populations. 3D biometrics are emerging technologies relevant for programs related to national ID, smart cities, and automated surveillance. It can be concluded that 3D biometric traits are reliable and secure but also exhibit adaptiveness for next-generation human identification systems capable of satisfying current security and usability requirements. Advanced sensors, machine learning models, and multimodal fusion tactics will ensure the future evolution of 3D biometrics with improved accuracy, scalability, and resilience towards spoofing while addressing user-centered, operational, and ecological real-world implications. Hand geometry recognition benefits through depth sensors that enable measurements of finger lengths, widths, and palm measurements from a distance, i.e., non-intrusively, and quickly, while satisfying access control for unsecure environments. Though hand geometry is not as unique as face or iris modalities, it achieves a useful accuracy level of about 90% and is highly accepted by users for comfort and ease of use. 3D fingerprint recognition add a depth dimension to the ridge patterns, highlighting depth differences in features to provide more discriminating features that can differentiate even identical twins, which a 2D fingerprint was unable to accomplish. Furthermore, laser scanning and photometric stereo achieve proper mapping of ridges so that depth is preserved. Deep learning frameworks continually improve automated minutiae extraction, and average recognition accuracy is about 93% under controlled testing conditions. Iris recognition using near-infrared 3D imaging achieves very high accuracies often exceeding 97%, which is attributed to the complex volumetric structure of the iris and the resistance of the iris structure from aging processes.

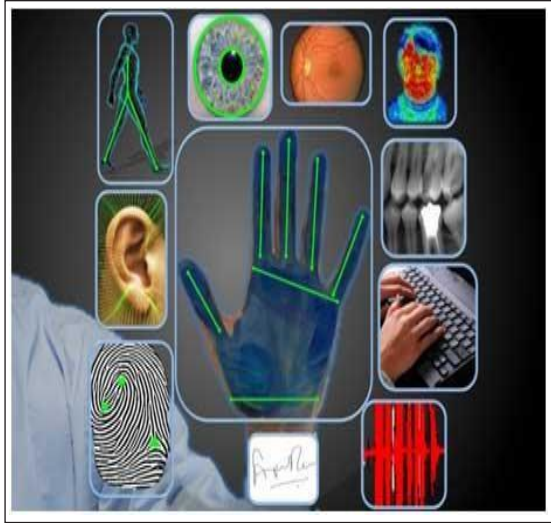


Fig. 5

VI. CONCLUSION

The study of 3D biometric characteristics emphasizes the increasing role of transformative identification systems which offer capabilities beyond traditional two-dimensional approaches. 3D biometric traits such as depth, texture, and surface structure offer improved accuracy and lower potential for spoofing, while remaining reliable across variable environments. 3D face, ear, palm, iris, and gait characteristics exhibit significant potential in real-world environments, including but not limited to forensic, security/surveillance, and access control applications. Notwithstanding, some of the challenges which remain include computational costs, storage, and technology deployments for 3D biometrics. Overall, 3D biometric systems will offer a promising future for identification solutions, particularly as they can combine higher security with a more natural user experience which is convenient.



Fig. 6

Research on 3D biometrics supports their promising ability to reduce risk and enhance security in fields such as border and customs control, healthcare, and personal device security. With 3D biometric traits we obtain a capability that reduces credentials reliability on forgery and reduces environmental noise over conventional methods, thus improving identity verification. With continued research efforts and investment into optimizing 3D biometrics, it will help to catalyze the much desired balance of security needs and user experience.

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