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New In-air Signature Datasets

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***Abstract*— Compared to traditional biometric systems, in-air signatures are considered more robust and secure than classical pen paper. A few datasets capturing in-air signatures have been introduced, utilizing various devices such as the Leap Motion and the Microsoft Kinect sensor camera. However, these devices are not exempt from shortcomings and exhibit certain limitations. The expenses associated with their implementation and the requirement for technical proficiency in operating them present notable challenges for in-air signature analysis. Additionally, users may encounter difficulties in adapting their finger movements to fit within the device's limited field of view, particularly if they lack familiarity with these devices. To address these concerns, this paper proposes the creation of three in-air signature datasets using solely the camera of a laptop or a smartphone, eliminating the need for any additional specialized equipment. Our datasets were collected in three ways. The first is the In-Air Signature dataset (IAS dataset) and the second is the In-Air Signature dataset using a transparent Glass Plate (IASGP dataset) while the third is the In-Air Signature dataset using Smart Phone (IASSP dataset). Forty volunteers participated in the construction of these datasets. Their ages ranged from 21 to 40 years. Each volunteer signs in the air five signatures and imitates five signatures of five other volunteers. Our in-air signatures datasets are publicly available and can be used for various research tasks like in-air signature verification and identification.**

Keywords*— *in-air signature dataset, genuine, forgery, verification, identification.

I. Introduction

Biometric systems are categorized into three branches: 1) Physiological biometrics refer to physical measurements of the human body like the fingerprint, iris and face [1]–[6]. 2) Behavioral biometrics refer to the measure of uniquely identifying and measurable patterns in human activities like keystroke dynamics, gait, voice and handwriting [7]–[16]. 3) Organic biometrics refer to the biological analysis of human bodies such as DNA and saliva [17], [18]. Based on these different biometric modalities, we will focus on behavioral biometrics and, more precisely, the signature task. In fact, the latter is an important biometric attribute, occupying a very special position in biometric systems.

The signature is one of the most common methods of verifying someone's identity by the general public and governmental institutions [19]. The counterfeit can be classified as easy if the forger makes no effort to imitate the signature, as random if the forger uses his own signature instead of the authentic one, or as freehand or expert if the forger makes an exact copy of the signature [20]. The acquisition mode of the signature can be categorized into three types. 1) offline, where only a scanned image of the signature trajectory is available [21], 2) online, where the pen movement of the signature over time is available [22] and 3) in-air which permits a person to sign in the air by allowing free hand movements [23].

According to several researchers, the in-air signature will have many potentials uses in the identification and verification of the person. In addition, the in-air signature will be used in many applications like access control. The in-air signature is considered one of the principal user biometric identifiers in a contactless mode allowing users identification by drawing their handwritten signature in the air [24] [25] [26].

Indeed, there are a few in-air signature datasets have been proposed. All of them use different devices to capture the in-air signatures like the Leap Motion and the Microsoft Kinect sensor camera. However, these devices are not without flaws and have certain limitations. High implementation costs and the need for technical expertise in their use pose significant obstacles to in-air signature analysis. Moreover, users may find it difficult to adjust their finger movement within the device's field of view, as they may not be well acquainted with the analysis system. In this paper, we propose three in-air- signatures datasets using only a camera of a laptop or a Smart Phone without any other specific device. We make these three in-air- signatures datasets available to the research community.

The rest of this paper is organized as follows. Section 2 describes a selection of existing in-air signature datasets. Section 3 presents our proposed in-air signature datasets. Finally, Section 4 concludes the paper.

II. OVERVIEW OF EXISTING IN-AIR SIGNATURE DATASETS

The recognition of in-air hand movements is complicated. Consequently, the process of collecting signatures in the air from the volunteers is very difficult and requires a great effort [27]. For this reason, a few in-air signature datasets have been proposed. Among these, we can cite the dataset created by Guerra-Casanova et al., in [28]. In this dataset, fifty participants requested to make a signature in the air while holding the mobile phone. In [29], Bailador et al., established an in-air signature dataset collected from 96 volunteers. The participants were given a device with an in-built sensor and requested to do their in-air signatures. Jeon et al., in [30] collected a dataset using Microsoft Xbox Kinect sensor. Fifty subjects participated in the collection of this dataset containing five hundred video clips of in-air signatures.

To collect a new in-air signature dataset, Takeuchi et al., in [31] used a Kinect depth camera. 100 volunteers participated in the creation of this database. The authors recorded for each in-air signature the motion time series in 3-dimensional data (X, Y, and Z). In [32], Nigam et al., created a new in-air signature dataset called IIITD LS database collected from 60 volunteers using Leap Motion. Another dataset is created by Sajid et al., in [33]. In this dataset, ten participants wearing Google Glass requested to make a signature in the air. Fang et al., in [34] created a new in-air signature dataset collected from 14 volunteers. Each volunteer signed 10 times. In addition, they recorded 30 forgeries for every original signer. The authors used a high-speed camera to record the fingertips. The signature files were saved in a text file containing the time sequence of the signature task which are X coordinates and Y coordinates.

Another dataset is created by Behera et al., in [35]. To create their dataset, the authors used a Leap Motion device. They involved 100 volunteers. Each volunteer signed 20 times. Malik et al., in [26] established a new in-air signature dataset called 3DAirSig collected from 15 volunteers. Each volunteer signed 15 times. In addition, they recorded 25 forgeries for every original signer from 5 impostors. In order to record the hand motion in 3D space from different viewpoints, the authors placed three GoPro cameras around the signer.

Behera et al., in [36] collected a dataset using Leap Motion performed by 50 participants. Each participant registered their signature 14 times. Therefore, a total of 700 signatures were collected. The authors created also another dataset containing 1600 in-air signatures using Leap Motion collected from 40 volunteers [37]. In [24], Khoh et al., created a new dataset called the Hand Gesture Signature (HGS) using a camera sensor Microsoft Kinect. Each hand gesture signature was captured as a video clip. Sixty-nine males and thirty-one females participated in the creation of this dataset.

In another work, Malik et al., in [38] collected a new dataset called DeepAirSig_Dataset included 40 volunteers. Jung et al., in [39] created a dataset containing signals distorted by the in-air handwritten signatures from 100 volunteers. The volunteers were asked to draw their signatures in the air while sitting at two different positions. At each position, the volunteers were requested to face four different directions which are front, right, left and back. A total of 8000 samples were collected in this dataset. In [40], Guerra-Segura et al., created a new in-air signature dataset containing 2000 signatures collected from 100 subjects. Li et al., in [41] created a new in-air signature dataset using the smartwatch motion sensors collected from 22 participants.

All the presented in-air signature datasets are summarized in Table I.

III. PROPOSED IN-AIR SIGNATURE DATASETS

We propose three datasets of in-air- signatures collected in three ways. The first is the In-Air Signature dataset (IAS dataset) and the second is the In-Air Signature dataset using a transparent Glass Plate (IASGP dataset) while the third is the In-Air Signature dataset using Smart Phone (IASSP dataset).

To create our new in-air signature datasets, we developed two systems on laptops and smartphones that can forecast human hand movement from a single RGB video image in real time. Indeed, the human hand is an illustrative illustration of an articulable entity with many characteristics, degrees of freedom, self-similarity, and self-occlusion [42]. Estimating the position of a moving hand is a difficult job in the field of human-computer interface [43]. For this reason, many frameworks are proposed by researchers like Modeep [44] and MediaPipe Hands framework [45]. To detect hand movement, we adopted the MediaPipe Hands framework[1], which provides precise finger and hand monitoring. Using Machine learning, MediaPipe Hands can determine 21 unique 3D locations on a hand from a single image. Moreover, the MediaPipe Hands framework runs at real-time speeds on a mobile device and can even accommodate users with numerous hands. MediaPipe Hands makes use of an ML pipeline that consists of several interconnected models: An image-wide model for detecting palms that provides a 3D enclosing frame for the hand in the correct orientation. High-fidelity 3D landmarks of the hand are returned by this model, which works on the compressed area of the picture as specified by the palm detector. By giving the hand landmark model a hand picture that has been precisely trimmed, the network is spared the burden of attempting to adjust the data in other ways (such as through rotations, translations, or scaling) and can instead focus on making precise predictions about the hand's coordinates. Our systems allow us to record the images and the coordinates x(t) and y(t) to be produced using the hand landmarks from the previous frame, and palm recognition is only activated to relocalize the hand. Our hand landmark model uses regression, or direct coordinate prediction, to precisely localize 21 3D hand-knuckle coordinates within the identified hand areas as shown in Figure 1.

Our systems allow volunteers to sign in the air easily and without any complication. The user can use his right hand or his left hand in the signing process. We use the index fingertip number 8 from the hand landmarks illustrated in Figure 1 during the recording of signatures in the air. Figure 2 presents an example of in-air signature acquisition.

[1] https://mediapipe.dev

TABLE I. SUMMARIES OF THE PRESENTED IN-AIR SIGNATURE DATASETS

Dataset	Number of users	Device	Number of signatures	Advantages	Weaknesses
Dataset of Guerra-Casanova et al., *[28]*	50	3-D accelerometer	2350	Gathering data from 50 users facilitates a more extensive and comprehensive analysis of the in-air signature identification and verification system.	In addition to the financial implications, 3D accelerometers are susceptible to noise interference, which can impact the accuracy of the measurements. External factors such as vibrations and electromagnetic interference can introduce noise.
Dataset of Bailador et al., *[29]*	96	Embedded accelerometer mobile device	768	By incorporating 96 participants, a more comprehensive analysis of the in-air signature identification and verification system becomes feasible.	Embedded accelerometers may have limited spatial resolution, meaning they may not be able to accurately measure small or subtle movements or vibrations. This can restrict their effectiveness in applications requiring high precision.
Dataset of Jeon et al., *[30]*	50	Microsoft Xbox Kinect sensor	500	The incorporation of a substantial number of participants facilitates a comprehensive analysis of the in-air signature identification and verification system. This extensive participant pool allows for a more in-depth examination and evaluation of the system's performance and effectiveness.	The Microsoft Xbox Kinect sensor is designed primarily for stationary use, typically placed on a flat surface or mounted on a stand. Its lack of portability and flexibility can limit its applications in scenarios that require mobility or capturing movements in different locations or angles.
Dataset of Takeuchi et al., *[31]*	100	Kinect depth camera	2000	By collecting data from 100 users, the analysis of the in-air signature identification and verification system can be conducted more comprehensively.	The limitation of this dataset is the cost associated with the usage of a Kinect depth camera.
IIITD Leap Signature Dataset *[32]*	60	Leap Motion	900	The IIITD LS Database is prepared in ambient indoor lighting with no occlusion of either the sensor or the subject's hand.	The Leap Motion may have limitations when it comes to detecting and accurately tracking precise and subtle finger movements or intricate hand.
SIGAIR dataset *[33]*	10	Google-Glass	96	The dataset encompasses hand movements captured in a three-dimensional space.	The limited number of participants and the cost of using Google Glass
Dataset of Fang et al., *[34]*	14	High-speed camera	560	Real-time fingertip tracking by the authors improved the Tracking Learning Detection algorithm.	The limited number of subjects may not fully capture the variability and diversity of real-world in-air signatures.
Air Signature DataSet_ICPR *[35]*	100	Leap motion interface	2000	The large number of participants allows for a more comprehensive analysis of signature recognition and verification algorithms, as it captures a wide range of individual variations in signature execution and style.	Participants may find it difficult to adjust their finger movement within the field of view of the Leap motion, as they may not be well acquainted with the system.
3DAirSig *[26]*	15	Three GoPro cameras	600	The dataset contains the hand motion in 3D space from different viewpoints.	The limited number of participants and the cost of using three GoPro cameras, along with any necessary accessories such as mounts, memory cards, and batteries, can add up significantly. This can be a barrier for individuals or organizations with limited budgets.
Dataset of Behera et al., *[36]*	50	Leap Motion	600	The dataset encompasses hand movements captured in a three-dimensional space.	In addition to the financial implications, the Leap Motion controller's performance can be affected by factors such as lighting conditions, reflective surfaces, and background clutter.
Dataset of Behera et al., *[37]*	40	Leap Motion	1600	The dataset contains hand movements captured in three-dimensional space.	Apart from the financial cost associated with using Leap Motion, the latter can be sensitive to occlusion, where objects or other body parts obstruct the view of the hands. This can lead to inaccurate or incomplete tracking when hands are partially or fully hidden from the device.
HGS dataset *[24]*	100	Microsoft Kinect sensor camera	2000	The inclusion of a large number of participants enables a more thorough analysis of the in-air signature identification and verification system.	The Microsoft Kinect sensor camera relies on infrared and depth-sensing technology to track movements. However, factors such as low lighting conditions, bright sunlight, or reflective surfaces can impact its performance.
DeepAirSig_Dataset *[38]*	40	Senz3D depth camera	1800	The dataset comprises 3D hand motions captured from various viewpoints.	One limitation of using the Senz3D depth camera is its cost, which may be a factor for some users or organizations with budget constraints.
Wi-Fi in-air signature dataset *[39]*	100	Wi-Fi-based in-air handwritten signature signals	8000	To examine the influence of geographical locations, the dataset was gathered at a distinct site, with the user positioned between the transmitting (Tx) side and the receiving (Rx) side.	The dataset contains a limited number of samples acquired from a single orientation at each position, which may not fully capture the variations in in-air Wi-Fi handwritten signatures at different positions and orientations
Dataset of Guerra-Segura et al., *[40]*	100	Leap motion	2000	Collecting data from a sample of 100 users enables a more thorough analysis of the in-air signature identification and verification system.	In addition to the financial implications, utilizing Leap Motion can involve certain drawbacks. Participants may find it difficult to adjust their finger movement within the field of view of the Leap motion, as they may not be well acquainted with the system.
Dataset of Li et al.,*[41]*	22	Smartwatch motion sensors	2465	The dataset contains hand movements captured in three-dimensional space.	The constrained number of subjects may not adequately encompass the wide range of variations and diversity present in real-world in-air signatures.

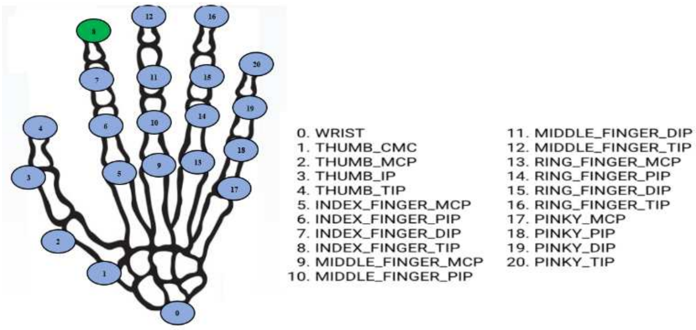


Fig. 1. Hand landmarks extracted from MediaPipe Hands framework

Fig. 2. Example of in-air signature acquisition

Forty subjects voluntarily participated in the database construction. The participants had normal or corrected-to-normal vision. Their age ranged from 21 to 40 years. Table II shows the characteristics of the participants in data collection.

During in-air signature data acquisition, participants were seated in a comfortable chair directly in front of the camera leaving a distance of 60 cm between their dominant hand and the camera. The participants were asked to close all the fingers of the hand leaving only the index finger. After that, they were requested to perform their signature in the air at their preferred speed. After completing the signature, the participants were asked to open all the fingers of the used hand. The purpose of this protocol is to control the beginning and the end of the signature in the air. To ensure that the participants had well understood the requested task, the experimenter displayed the task. The participants were allowed to practice the task before recording the data for five minutes. Custom-made software developed in Python for laptops and a mobile application with Android studio for smartphones were used to record the data.

- The first is a CSV file that contains the coordinates of the signature in the air (x(t) and y(t)).

- The second is a jpg file that contains the image of the signature.

TABLE II. CHARACTERISTICS OF PARTICIPANTS IN DATA COLLECTION

Total number of samples collected		40
Men		31
Women		9
Age	**21-23**	10
	24-27	8
	28-30	8
	31-35	7
	36-40	7
Right hand		32
Left hand		8

Each volunteer signs in the air five signatures and imitates five signatures of five other volunteers. Table III provides a brief description of the datasets created.

TABLE III. DETAILS OF OUR IN-AIR SIGNATURE DATASETS

	Signature type	**Number of signatures**
In-Air Signature dataset (IAS dataset)	Genuine	200
	Skilled forgeries	200
In-Air Signature dataset using a transparent Glass Plate (IASGP dataset)	Genuine	200
	Skilled forgeries	200
In-Air Signature dataset using Smart Phone (IASSP dataset)	Genuine	200
	Skilled forgeries	200

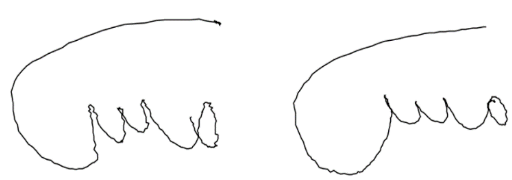
In the following, we present our three proposed datasets.

A. *In-Air Signature dataset (IAS dataset)*

Figure 3 presents an example of data acquisition for IAS dataset.

Fig. 3. Example of data acquisition for IAS dataset

Figure 4 displayed examples of genuine and forgery in-air signatures extracted from the IAS dataset for the same user.



(A) **(B)**

Fig. 4. Examples of in-air signatures extracted from IAS for the same user (A): genuine in-air signatures, (B): forgery in-air signatures

B. In-Air Signature dataset using Glass Plate (IASGP dataset)

The experimental protocol for IASGP dataset acquisition is the same as in the IAS dataset. The only difference is that we put a transparent glass plate in front of the camera away 30 cm. This glass plate, with dimensions of 60 cm in both length and width, is placed inside a wooden frame and fixed on the table in front of the volunteers as shown in Figure 5.

Fig. 5. Example of data acquisition for the IASGP dataset

C. In-Air Signature dataset using Smart Phone (IASSP dataset)

Our In-Air Signature dataset using Smart Phone (IASSP dataset) permits us to record the coordinates of the signature in the air (x(t) and y(t)) from our mobile application. During in-air signature data acquisition, participants were seated in a comfortable chair directly in front of the camera of Smart Phone leaving a distance of 7 cm between their dominant hand and the camera.

Figure 6 presents an example of data acquisition for the IASSP dataset.

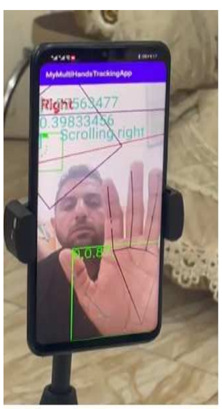


Fig. 6. Example of data acquisition for the IASSP dataset

IV. Conclusion

We presented in this paper three datasets of in-air signatures collected in three ways. In the IAS dataset, the volunteer signs in the air directly in front of the camera of the laptop. In the IASGP dataset and to make the task more challenging, the volunteers sign in the air with a transparent Glass Plate between them and the camera. In the IASSP dataset, the volunteers sign in the air using Smart Phone. Our in-air signatures datasets are publicly available after contacting the authors and signing a user agreement. These datasets can serve as a foundation for further research and development in the field of in-air signature verification and identification. We plan to enlarge our datasets by adding other participants. Having a diverse set of users helps in evaluating the robustness and generalizability of the systems across different individuals that may have different writing habits, hand sizes, and motor skills. Furthermore, it is possible to capture other biometric modalities, such as the human face, while recording the in-air signing action. Therefore, the integration of these additional modalities with the signature through multimodal fusion is anticipated to enhance the performance of biometric systems.

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