



## RESEARCH ARTICLE

# REVISED In-air Hand Gesture Signature Recognition: An iHGS Database Acquisition Protocol [version 2; peer review: 2 approved, 1 approved with reservations]

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## Abstract

**Background:** With the advances in current technology, hand gesture recognition has gained considerable attention. It has been extended to recognize more distinctive movements, such as a signature, in human-computer interaction (HCI) which enables the computer to identify a person in a non-contact acquisition environment. This application is known as in-air hand gesture signature recognition. To our knowledge, there are no publicly accessible databases and no detailed descriptions of the acquisitional protocol in this domain.

**Methods:** This paper aims to demonstrate the procedure for collecting the in-air hand gesture signature's database. This database is disseminated as a reference database in the relevant field for evaluation purposes. The database is constructed from the signatures of 100 volunteer participants, who contributed their signatures in two different sessions. Each session provided 10 genuine samples enrolled using a Microsoft Kinect sensor camera to generate a genuine dataset. In addition, a forgery dataset was also collected by imitating the genuine samples. For evaluation, each sample was preprocessed with hand localization and predictive hand segmentation algorithms to extract the hand region. Then, several vector-based features were extracted.

**Results:** In this work, classification performance analysis and system robustness analysis were carried out. In the classification analysis, a multiclass Support Vector Machine (SVM) was employed to classify the samples and 97.43% accuracy was achieved; while the system robustness analysis demonstrated low error rates of 2.41% and 5.07% in random forgery and skilled forgery attacks, respectively.

**Conclusions:** These findings indicate that hand gesture signature is not only feasible for human classification, but its properties are also robust against forgery attacks.

## Keywords

Dynamic Signature, Hand Gesture Signature, Gesture Recognition, Hand Gesture Signature Database, Image Processing, Forgeries Attack

## Open Peer Review

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**REVISED Amendments from Version 1**

We are pleased to inform you that this updated version of the manuscript has incorporated all the feedback provided by the reviewers. Specifically, we have provided a detailed explanation of the hyperparameters used in our learning models, and we have thoroughly revised and elaborated on the discussion of classification and robustness performance analysis. Additionally, we have included the latest related work and updated the references accordingly. Moreover, two new figures, Figure 1 and Figure 2, which illustrate the iHGS sample acquisition process from both top and side views have been included in the manuscript. We believe that these figures will help clarify our methodology and improve the manuscript's overall readability. Furthermore, we have revised some statements as suggested by the reviewers to avoid any confusion or misleading information.

**Any further responses from the reviewers can be found at the end of the article**

**Introduction**

A conventional dynamic signature recognition usually uses a special digitized device to capture the dynamic properties of a signature. A stylus pen is used to sign the signature on the surface of the digital tablet. This leaves a subtle track, exposing the signature information to others. A forger could learn the pattern from what they obtained from the tablet surface.

Numerous acquisition approaches have been proposed to replace the usage of a tablet for dynamic signatures. For instance, two ballpoint pens with sensors to measure the pen movement during the signing process,<sup>1</sup> a wearable device on the wrist (i.e. smartwatches) to capture the hand motion,<sup>2</sup> or an on-phone triaxial accelerometer built in a smartphone.<sup>3,4</sup>

The introduction of low-cost sensor cameras<sup>5</sup> brings up new research opportunities for contactless human-computer interaction (HCI) in various applications such as robotics, healthcare, entertainment, intelligent surveillance, and intelligent environments.<sup>6</sup> Human hand gestures and dynamic signature recognition are becoming prevalent. This work proposes a hand gesture signature recognition system with the capability to recognize the identity of a person in a touchless acquisition environment. Additionally, a public database is provided for evaluation purposes.

Some relevant research works have been conducted using their own collected database. Tian et al.<sup>7</sup> introduced a Kinect-based password authentication system to explore the feasibility of a Kinect sensor to authenticate user-defined hand gesture passwords. In Ref. 8, the authors proposed a similar hand gesture signature recognition where the hand trajectory was used as the feature. The performance was evaluated on a self-collected database, consisting of 50 different classes. Empirical results demonstrated the feasibility and benefits of depth data in verifying a user's identity based on a hand gesture signature. Fang et al.<sup>9</sup> proposed a fusion-based in-air signature verification. The user's fingertip was tracked and the signature trajectory was extracted from a video sample captured by a high-speed camera. Malik et al.<sup>10</sup> implemented a neural network in recognizing hand gesture signatures for identity authentication. A CNN-based hand pose estimation algorithm was employed to estimate the hand joint position for the index fingertip. Multidimensional dynamic time warping (MD-DTW) was adopted to match the template and test signature data. It was tested on a self-collected dataset with 15 classes. The empirical results exhibited a promising recognition performance with the presence of depth features. Li and Sato<sup>11</sup> proposed an in-air signature authentication using the motion sensors of smart wrist-worn devices. The system captures signal-based gyroscope and accelerometer measurements employs a recurrent neural network (RNN) to classify between genuine and imposter hand signatures of twenty-two (22) participants. The research reported a highly promising equal error rate (EER) of only 0.83%. However, this research only tested the random forgeries of the signature.

From the literature, the existing studies were mainly utilizing their self-collected databases. To the best of our knowledge, there is no publicly available hand gesture signature database. The existence of a publicly available database can provide a freely available source of data to encourage more researchers into the field. For this reason, we present an openly available database, collected by the Microsoft Kinect sensor camera. To protect the privacy of the contributors, only depth information will be shared.

**Database collection**

A Microsoft Kinect sensor camera is used as the main acquisition device to collect the samples of in-air hand gesture signature (iHGS) via its built-in IR projector and IR camera. A sample is a video clip that contains a set of image sequences disclosing the hand movement of a signature signing. The Kinect camera is capable of capturing up to 30 depth frames per second (fps). The number of image sequences (frames) of each sample corresponds to the duration of the hand movement and might be varying in each signature. Additionally, other computational factors such as heavy graphical processing and input latency affect the fps in each enrollment. These latencies may lead to a drop in the rate of fps, causing

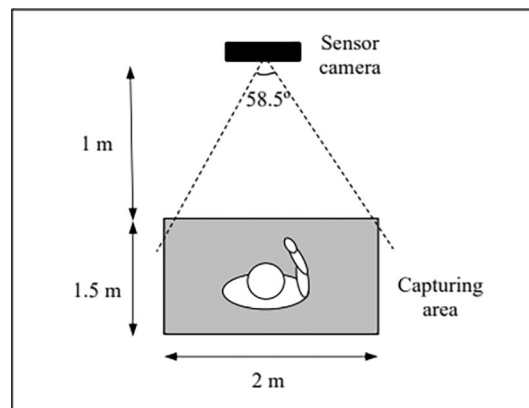
information loss. Thus, to ensure validation, the collected samples that have a fps rate of less than 27 are dropped/removed and the sample is re-captured through a similar procedure again. Figure 1 and Figure 2 depict the implementation of the iHGS sample acquisition process from both top and side views. The distances and spaces between the sensor camera and the subject were carefully chosen to ensure the entire body could be captured during the acquisition process. A more detailed data acquisition protocol can be found in Ref. 12.

The database is named *iHGS database*. The data collection was conducted in two separate sessions and the entire process took four months to complete. Samples for the second session were collected with a time interval of approximately two to three weeks from the first session. This arrangement is intended to allow the intra-variances in genuine hand gesture signatures, better reflecting real-world situations. Before enrolment, the flow of the entire enrolment process was explained to each participant. They were given ample time to practice and familiarize themselves with the process before data acquisition.

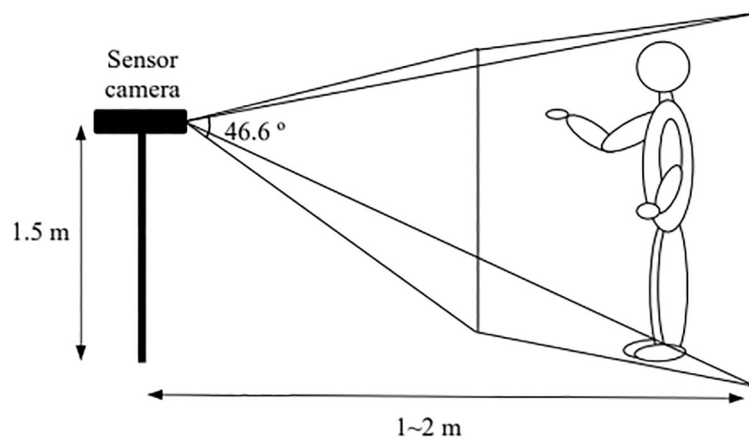
A total of 100 participants were successfully enrolled. Among the participants, 69 were male and 31 female, aged from 18–40 years. 90% of participants were right-handed (signing with their right hand) with only 10% using their left hand (left-handed). Table 1 summarizes the characteristics of the iHGS database.

There are two subsets of our *iHGS database*: (1) *genuine dataset*, and (2) *skilled forgery dataset*. For genuine dataset, each participant provides 10 genuine samples in each session (session 1 and session 2). A total of 2000 ( $10 \times 2 \times 100$ ) samples were gathered for this genuine dataset.

A skilled forgery dataset contains forged signature samples. Each forger was provided with one genuine signature sample (signed by the genuine user on a piece of paper) randomly. They were asked to learn the signature with as much time as



**Figure 1.** The top view of iHGS sample acquisition.



**Figure 2.** The side view of iHGS sample acquisition.

**Table 1. Characteristics of hand gesture signature samples in the iHGS database.**

Total number of participants		100	
Male		69	
Female		31	
Age	18-19	12	
	20-25	68	
	26-30	8	
	31-35	11	
	36-40	1	
Right-handed		90	
Left-handed		10	
Frame Rate		27-30 fps	
No. of frame/signature	Genuine	Min	20
		Max	304
		Average	72.4
	Forgery	Min	21
		Max	294
		Average	76.6

**Table 2. Summary of the number of hand gesture signatures for genuine and skilled forgery datasets.**

Dataset		No. of samples
Genuine dataset	Total number of participants	100
	Number of samples/participants	20
	<b>Total samples</b>	<b>2000</b>
Skilled forgery dataset	Total number of forgers	98
	Number of forgery samples/forger	10
	<b>Total forgery samples</b>	<b>980</b>

they needed. Then, each forger was asked to imitate the assigned signature 10 times. A total of 1000 skilled forgery signatures were successfully collected. However, 20 skilled forgery samples from two forgers (10 samples each) were corrupted due to the hardware error. Thus, only 980 skilled forgery samples were obtained. Table 2 summarizes the number of hand gesture signatures for the two subsets in the *iHGS database*.

## Methods

### Data preprocessing

Hand detection and localization techniques were applied to extract the region of interest (ROI) from each of the depth images of the *iHGS database*. A predictive hand segmentation technique was performed to precisely extract the hand region from the frames. Refer to Refs. 12, 13, 14 for more information.

### Feature generation

An *iHGS* sample is a collection of depth image sequences that comprises of  $n$  image frames, i.e.  $n$  is also the length of the sample. Several basic vector-based features are extracted from the sample. Firstly, a Motion History Image (MHI) process is performed on the preprocessed depth image sequence of each sample along the time. This technique effectively condenses the image sequence into a single grey-scale image (coined as *MHI* template), while preserving the motion information in a more compact form.<sup>15,16</sup> Specifically, *MHI* template describes the hand location and motion path along the time and generates a spatio-temporal information for the *iHGS* sample. The *MHI* image is then transformed into a vector space to produce a vector-based feature. The features explored in this work are as follows:

(a) *x-directional summation* ( $V_X$ )

Produced by summing the *MHI* template in the vertical direction.

(b) *y-directional summation* ( $V_Y$ )

Produced by summing the *MHI* template in the horizontal direction.

(c) *xy-directional summation* ( $V_{XY}$ )

The concatenation of both  $V_X$  and  $V_Y$  features for a richer one-dimensional summation feature.

(d) Histogram of Oriented Gradient feature ( $V_{HOG}$ )

A histogram descriptor is performed on the *MHI* template to extract the local texture, represented in a distribution of the edge and gradient structure.<sup>17</sup> It can discover the shape or the outline of the template image based on the slope or orientation gradient. It is worth noted that each pixel value in the *MHI* template describes the motion's temporal information at a particular location. Thus, histogram orientation of the *MHI* template represents the intensity of motion history which is a useful feature.

(e) Binarized Statistical Image Features ( $V_{BSIF}$ )

Statistical-based features are computed and summarized in a single histogram representation. First, the input image is convolved with a set of predefined filters to maximize the statistical independence of the filter responses.<sup>18</sup> Then, each response is applied to a nonlinear hashing operator to improve the computational efficiency. Next, the generated code map is regionalized into blocks and recapitulated into a block-wise histogram. These regional histograms are lastly concatenated into a global histogram, representing the underlying distribution of the data. In this work, different BSIF-based features are produced:

- $V_{BSIF-MHI}$  – *MHI* template is used as input data to the BSIF.
- $V_{BSIF-X}$  – Image sequences of an iHGS sample are projected along the *y*-axis to generate an *X-Profile* template. *X-Profile* template is used as input data to the BSIF.
- $V_{BSIF-Y}$  – Image sequences of an iHGS sample are projected along the *x*-axis to generate the *Y-Profile* template. *Y-Profile* template is used as input data to the BSIF.
- $V_{BSIF-XY}$  – Both *X-Profile* and *Y-Profile* templates are used as the data input to the BSIF.
- $V_{BSIF-MHIXY}$  – *MHI*, *X-Profile*, and *Y-Profile* templates are used as the data input to the BSIF.

## Experimental results

Two types of performance analyses are conducted: (1) *classification performance analysis*, and (2) *robustness analysis against forgery attacks*. A well-known multiclass Support Vector Machine (SVM) is adopted in the classification analysis through a One-versus-One (OVO) approach. The genuine dataset is randomly divided into a training set and a testing set with a ratio of  $m:n$  where  $m$  is larger than  $n$ . The training set is further partitioned into two subsets: validation subset and training subset with the ratio of  $m_p:n_p$ . The training subset is to train the SVM model; while the validation subset is to find the optimal model parameters for a minimal validation error. The model is then tested on the testing set for performance evaluation. The robustness performance analysis measures the security level against impersonation attempts. It demonstrates two attacks: random forgery and skilled forgery. In the former, a testing sample that belongs to a subject  $i$  is compared with all the remaining samples of other subjects in the genuine dataset. In the latter, a forged sample of a subject  $j$  (from the skilled forgery dataset) is matched with a claimed identity's sample (i.e., genuine subject  $i$ 's sample) from the genuine dataset.

### Classification performance analysis

This analysis is implemented using the multi-class classification feature which is available in a library of SVM (LIBSVM) in MATLAB.<sup>19</sup> The samples of the genuine dataset are randomly partitioned into training, validation, and testing subsets, refer to Table 3.

**Table 3. Data distribution in SVM classifier analysis.**

<b>Genuine dataset</b>	Training samples	1000
	Validation samples	400
	Testing samples	600
	Total	2000

A polynomial kernel of the SVM classifier is utilized as part of our machine learning model. The samples were randomly partitioned into training, validation and testing subsets to evaluate the model's performance. For cross-validation purposes, we repeated this random partitioning process five times using five different subsets. The hyperparameters for the polynomial kernel are tuned as such that the gamma ( $\gamma$ ) is set to 20, the degree of the polynomial ( $d$ ) is set to 2 and the cost ( $C$ ) is set to 1. These hyperparameters were determined through empirical testing, and the settings that proposed yielded optimal and stable performance across our multiple experiments were used. The averaged classification measurements including *precision*, *recall*, *specificity*, and *F1-score* and the standard deviation are reported in [Table 4](#). The accuracies among features are illustrated in [Figure 1](#).

The classification results show the two BSIF features,  $V_{BSIF-XY}$  and  $V_{BSIF-MHIXY}$  achieving the best accuracy scores of 97.43% and 93.57%, respectively. It is followed by the HOG feature  $V_{HOG}$  with an accuracy of 91.63%. It is noted that the system vaguely classifies the summation features,  $V_X$  and  $V_Y$  with accuracies of 61.43% and 61.20%. However, there is a boost in performance when concatenating them together, achieving 86.63% classification accuracy.

The results found that certain vector-based features such as  $V_{BSIF-XY}$  and  $V_{BSIF-MHIXY}$ , possess high levels of discriminative information for classifying in-air hand gesture signatures. Compared to other methods that involve complex preprocessing, the proposed vector-based features are extracted directly from the raw data, without the need for sophisticated techniques. These features can be used directly for classification model training, such as the SVM model, making it more convenient for real-world applications. Furthermore, the small value of standard deviation associated with these features suggests a high degree of stability in predicting hand gesture signatures. This is important in any classification task, as it ensures that the classification algorithm produces consistent and reliable results across a range of input data. The stability of these features is especially valuable in applications where the quality and consistency of the input data may vary. In summary, our findings demonstrate that vector-based features, particularly  $V_{BSIF-XY}$  and  $V_{BSIF-MHIXY}$ , offer a robust and reliable approach to iHGS classification. These features are easy to use and require minimal preprocessing, making them ideal for real-world applications that require efficient and accurate classification algorithms.

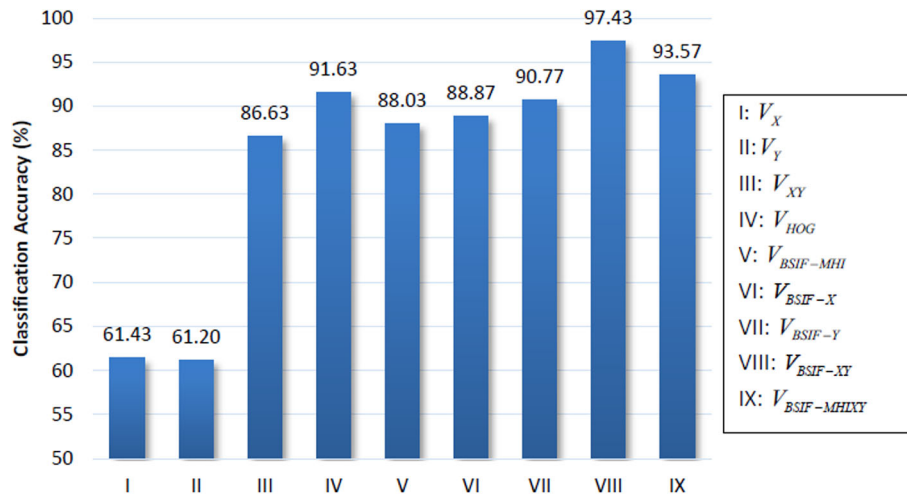
### Robustness performance analysis

This experimental analysis aimed to determine the robustness of the proposed approach against two types of forgery attacks, namely random forgery attacks and skilled forgery attacks.

The experiments were repeated for five trials. Averaged equal error rate (EER) and standard deviations were recorded. Four distance metrics were examined: Euclidean distance (*EucD*), Cosine distance (*CosD*), Chi-Square distance (*CSqD*), and Manhattan distance (*MD*).

**Table 4. Performances of precision, recall, specificity, and f1-score for polynomial kernel SVM.**

Feature notation	Prec.	Recall	Spec.	F1-score
$V_X$	63.82 ± 2.51	61.43 ± 2.00	99.61 ± 0.02	60.44 ± 2.19
$V_Y$	64.94 ± 2.60	61.20 ± 2.15	99.61 ± 0.02	60.59 ± 2.19
$V_{XY}$	88.45 ± 1.14	86.63 ± 1.16	99.87 ± 0.01	86.44 ± 1.32
$V_{HOG}$	93.14 ± 0.70	91.63 ± 1.05	99.92 ± 0.01	91.63 ± 1.07
$V_{BSIF-MHI}$	89.53 ± 1.32	88.03 ± 1.40	99.88 ± 0.01	87.83 ± 1.45
$V_{BSIF-X}$	90.50 ± 1.48	88.87 ± 1.67	99.89 ± 0.02	88.74 ± 1.66
$V_{BSIF-Y}$	92.20 ± 0.91	90.77 ± 0.77	99.91 ± 0.01	90.60 ± 0.83
$V_{BSIF-XY}$	97.80 ± 0.30	97.43 ± 0.35	99.97 ± 0.00	97.42 ± 0.33
$V_{BSIF-MHIXY}$	94.63 ± 0.56	93.57 ± 0.63	99.94 ± 0.01	93.55 ± 0.58



**Figure 1. Classification accuracies of polynomial kernel SVM.**

Tables 5 and 6 report the system performances of two forgery attacks. It can be seen that the performances of the four kinds of distance metrics vary with different feature vectors. For the random forgery attack,  $V_{HOG}$  with a cosine distance metric yields the lowest EER in random forgery (EER-R) of 2.41% followed by  $V_{BSIF-MHIXY}$  with EER-R of 5.18%. Manhattan distance is not able to perform in this context as compared with the other metrics.

Distinguishing skilled forgery attacks from genuine signatures is undeniably more challenging than detecting random forgery attacks, due to the high similarity between the forgery and genuine samples. Consequently, the Equal Error Rates (EERs) for skilled forgery attacks are expected to be higher than for random forgery attacks. Our study found that the vector-based features  $V_{xy}$  and  $V_{HOG}$ , when adopted with the cosine distance metric, achieved the best EER-S of 5.07% for skilled forgery attacks. This is a promising result, and it proves that these features can be effective in distinguishing skilled forgeries from genuine signatures.  $V_{BSIF-MHIXY}$  with the Euclidean distance metric, obtained an EER-S of 9.45%, which is also a relatively good result. On the other hand, most BSIF features were found to perform poorly in verifying skilled forged hand gesture signatures, highlighting the importance of carefully selecting the features used for authentication. Similar to random forgery attacks, the Manhattan distance metric achieved the worst performance. Again, it indicates that the selection of the right distance metric is crucial for achieving good verification performance. In summary, these findings demonstrate that the verification performance of iHGS is not solely determined by the extracted features but is also highly dependent on the choice of distance metric. Therefore, careful consideration must be given to both factors in verifying the iHGS.

**Table 5. EER for random forgery attack (EER-R).**

Feature notation	EER-R (AVG% ± STD)			
	<i>EucD</i>	<i>CosD</i>	<i>CSqD</i>	<i>MD</i>
$V_x$	14.33 ± 0.16	8.64 ± 0.35	10.36 ± 0.21	15.01 ± 0.41
$V_y$	11.87 ± 0.30	7.33 ± 0.30	8.54 ± 0.33	13.08 ± 0.22
$V_{xy}$	10.58 ± 0.22	2.91 ± 5.07	6.62 ± 0.11	11.55 ± 0.32
$V_{HOG}$	21.96 ± 0.34	<b>2.41 ± 0.22</b>	19.49 ± 0.66	25.74 ± 0.24
$V_{BSIF-MHI}$	5.94 ± 0.37	6.35 ± 0.28	9.88 ± 0.21	13.00 ± 0.30
$V_{BSIF-x}$	10.51 ± 0.37	9.44 ± 0.69	7.99 ± 0.49	12.09 ± 0.44
$V_{BSIF-y}$	10.10 ± 0.57	10.33 ± 0.24	9.92 ± 0.41	14.02 ± 0.19
$V_{BSIF-xy}$	8.84 ± 0.43	7.01 ± 0.39	7.86 ± 0.56	12.19 ± 0.28
$V_{BSIF-MHIXY}$	5.18 ± 0.28	5.43 ± 0.10	7.49 ± 0.26	11.15 ± 0.32



**Table 6. EER for skilled forgery attack (EER-S).**

Feature notation	EER-S (AVG% ± STD)			
	<i>EucD</i>	<i>CosD</i>	<i>CSqD</i>	<i>MD</i>
$V_x$	18.97 ± 0.25	15.00 ± 0.85	15.39 ± 0.42	19.44 ± 0.53
$V_y$	14.70 ± 0.37	10.31 ± 0.32	11.11 ± 0.23	15.47 ± 0.37
$V_{XY}$	15.01 ± 0.32	<b>5.07 ± 0.23</b>	10.25 ± 0.43	16.87 ± 0.22
$V_{HOG}$	25.69 ± 0.32	<b>5.07 ± 0.53</b>	24.42 ± 0.58	29.71 ± 0.42
$V_{BSIF-MHI}$	9.45 ± 0.64	10.43 ± 0.43	15.40 ± 0.60	19.62 ± 0.46
$V_{BSIF-x}$	20.59 ± 0.50	18.64 ± 0.87	19.39 ± 0.63	23.62 ± 0.81
$V_{BSIF-y}$	16.52 ± 0.60	16.55 ± 0.73	16.39 ± 0.43	20.87 ± 0.28
$V_{BSIF-XY}$	16.16 ± 0.67	13.99 ± 0.61	15.42 ± 0.41	21.59 ± 0.57
$V_{BSIF-MHXY}$	9.47 ± 0.67	9.84 ± 0.23	14.97 ± 0.20	19.00 ± 0.50

## Conclusions

In this paper, we presented a self-collected *iHGS database* and a detailed description of the acquisition protocol to collect the database. Several basic sets of vector-based features were extracted from the samples. This paper also investigated the effectiveness of classification capability as well as the robustness against forgery attacks. The experimental results for both analyses have shown promising results with the appropriate features extracted from the samples. Our analyses demonstrate the potential of *iHGS* in both recognition and verification. However, there is room for future exploration in *iHGS*. The current database was collected in a controlled environment. As a biometric authentication, other external factors such as angles of the camera, the distance between user and acquisition devices, different background complexity, etc should be considered. In particular, it could be further extended by considering those uncontrolled environmental factors to increase the challenge of the database.

## Data availability and materials

Figshare: In-air Hand Gesture Signature Database (*iHGS Database*) <https://doi.org/10.6084/m9.figshare.16643314>

This project contains the following underlying data:

- Genuine dataset (100 contributors labels with ID from 1 to 100)
- Skilled forgery dataset (98 contributors labels with ID from 1 to 100 where ID of 84 and 88 are not included)

Data are available under the terms of the [Creative Commons Attribution 4.0 International license](https://creativecommons.org/licenses/by/4.0/) (CC-BY 4.0).

## Ethics approval and consent to participate

The experimental analyses were established, according to the ethical guideline and were approved by the Research Ethics Committee (REC) with the ethical approval number EA1452021. Written informed consent was obtained from individual participants.

## Author contributions

W.H. carried out the experiment with support from Y.H. and H.Y. coordinated the data collection and establishment of the database. Besides, W.H. took the lead in writing the manuscript while Y.H. and H.Y. provided critical feedback and helped shape the analysis and manuscript.

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# Open Peer Review

Current Peer Review Status:   

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Version 2

Reviewer Report 18 August 2023

<https://doi.org/10.5256/f1000research.147166.r189966>

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**Paolo Roselli**

Università di Roma, Rome, Italy

**Jean Vanderdonckt**

Louvain School of Management, Universite catholique de Louvain, Louvain-la-Neuve, Walloon Region, Belgium

The short article briefly describes a particular way to collect in-air hand gesture signatures to produce a publicly accessible database of such in-air hand gesture signatures.

- Are sufficient details of methods and analysis provided to allow replication by others? I answered "partly" because:

1. It is not clear what "skilled" precisely means

2. It is not clear if the set of participants producing the "Genuine" dataset is disjoint from the set of forgers producing the "Skilled forgery" dataset

3. A visual example of in-air signature would have been appreciated

- If applicable, is the statistical analysis and its interpretation appropriate?

o I answered "partly" because in "Figure 1" I would have appreciated to see the confidence intervals

- Are the conclusions drawn adequately supported by the results?

o I answered "partly" because the term "human classification" is open to interpretations and applications too varied and potentially dangerous to humans to be simply considered as "feasible". The same consideration can be made about the claim "robust against forgery attacks".

**Is the work clearly and accurately presented and does it cite the current literature?**

Yes

**Is the study design appropriate and is the work technically sound?**

Yes

**Are sufficient details of methods and analysis provided to allow replication by others?**

Partly

**If applicable, is the statistical analysis and its interpretation appropriate?**

Partly

**Are all the source data underlying the results available to ensure full reproducibility?**

Yes

**Are the conclusions drawn adequately supported by the results?**

Partly

**Competing Interests:** No competing interests were disclosed.

**Reviewer Expertise:** Vector based gesture recognition; Mathematical Analysis; Clifford Geometric Algebra

**We confirm that we have read this submission and believe that we have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.**

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### Version 1

Reviewer Report 12 December 2022

<https://doi.org/10.5256/f1000research.77854.r126552>

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**Cheng-Yaw Low**

Institute for Basic Science, Daejeon, South Korea

This manuscript contributes a small-scale in-air hand gesture signature dataset to the research community.

However, this manuscript is overly simplified.

My concerns are as follows:

1. The authors should compare the new dataset to other repositories, e.g. the ones employed in Refs. 11, 12, etc. Despite of being private, these existing datasets should be at least introduced in the manuscript. Moreover, the main reason why this newly constructed dataset is important to iHGS should further be underlined.

2. I think some relevant illustrations should be provided?

3. Some parts in the Method section are not clear, e.g., the data preprocessing section, the feature dimensions for V\_HoG and V\_BSIF are not disclosed, etc.

4. The following statement is problematic?

*"The data distribution is randomized in five different trials using a polynomial kernel."*

Therefore, a revision is needed prior to indexing.

**Is the work clearly and accurately presented and does it cite the current literature?**

Yes

**Is the study design appropriate and is the work technically sound?**

Partly

**Are sufficient details of methods and analysis provided to allow replication by others?**

Partly

**If applicable, is the statistical analysis and its interpretation appropriate?**

Partly

**Are all the source data underlying the results available to ensure full reproducibility?**

Partly

**Are the conclusions drawn adequately supported by the results?**

Partly

**Competing Interests:** No competing interests were disclosed.

**Reviewer Expertise:** Biometrics, Pattern Recognition.

**I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.**

Author Response 26 Apr 2023

**Wee How Khoh**

We would like to express our sincerest gratitude to you and to all the reviewers for their constructive comments on our manuscript entitled "In-air Hand Gesture Signature Recognition: An iHGS Database Acquisition Protocol" and thanks for the opportunity to revise the paper. We have incorporated changes that reflect the detailed suggestions you have graciously provided. We also hope that our edits and the responses below satisfactorily address all the issues and concerns you and the reviewers have noted.

**1.** *"The authors should compare the new dataset to other repositories, e.g. the ones employed in Refs. 11, 12, etc. Despite of being private, these existing datasets should be at least introduced in the manuscript. Moreover, the main reason why this newly constructed dataset is important to iHGS should further be underlined."*

**Response:**

Thank you for your valuable feedback. We appreciate your comment in our manuscript and would like to clarify that the datasets mentioned in Refs. 11 and 12 are identical to ours in this manuscript. It's important to note that, to date, there are no publicly available in-air hand gesture signature datasets, which makes it challenging to compare our dataset to them. Our manuscript aims to address this gap in the literature by presenting the acquisition protocol used to build the dataset and share the dataset with the public. We hope that this will contribute to further research in this area. Thank you once again for your feedback.

**2.** *"I think some relevant illustrations should be provided?"*

**Response:**

Thank you for your comment. We have updated the manuscript accordingly. Figure 1 and Figure 2 have been included in the revised version to illustrate the iHGS sample acquisition process from both top and side views. We hope these figures will help clarify the methodology and improve the manuscript's overall readability.

**3.** *"Some parts in the Method section are not clear, e.g., the data preprocessing section, the feature dimensions for V\_HoG and V\_BSIF are not disclosed, etc."*

**Response:**

We agree that providing more details can enhance the understanding of our research. However, due to the page constraint of the current manuscript, we were unable to include all the necessary information and details. To address this, we have added a statement to the manuscript (in the section "Method"), directing readers to our previous research paper Ref. 12, 13 and 14, where a more comprehensive description of the methodology can be found.

**4.** *"The following statement is problematic?  
"The data distribution is randomized in five different trials using a polynomial kernel.""*

**Response:**

Thank you for your comment. We apologize for any confusion and misleading in the statement. We have revised the statement as follows:

**Revised texts:**

A polynomial kernel of the SVM classifier is utilized as part of our machine learning model. The samples were randomly partitioned into training, validation and testing subsets to evaluate the model's performance. For cross-validation purposes, we repeated this random partitioning process five times using five different subsets.

**Competing Interests:** No competing interests were disclosed.

Reviewer Report 30 March 2022

<https://doi.org/10.5256/f1000research.77854.r126550>

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**Lillian Yee Kiaw Wang** 

Monash University Malaysia, Subang Jaya, Malaysia

The article discussed how a self-collected iHGS database is built. The acquisition protocol is clearly described. The effectiveness of classification capability and robustness against forgery attacks are also discussed.

Some points for your consideration:

1. Some of the threshold values stated in the article should be supported by citation or justification on why that particular value is selected. For example:
  - "Thus, to ensure validation, the collected samples that have an fps rate less than 27 are removed and re-captured again" Needs citation or justification, why 27?
  - "The optimal hyperparameters for the polynomial kernel are tuned empirically such that the gamma ( $\gamma$ ) is set to 20, the degree of the polynomial ( $d$ ) is set to 2 and the cost ( $C$ ) is set to 1." Needs citation or justification, why the parameters were set as such?
2. The discussion of results for classification performance analysis is quite brief. Suggest to elaborate further on its impacts, for example, easy learning process and prediction stability -- easy or stable in what way? Also, apparent significance of your results compared to previous research works can be discussed in detail.
3. Similar comments for the discussion of results for robustness performance analysis (refer point 2).
4. More update-to-date references would be good, particularly references to support the discussions of result should be of recent research works.

**Is the work clearly and accurately presented and does it cite the current literature?**

Partly

**Is the study design appropriate and is the work technically sound?**

Yes

**Are sufficient details of methods and analysis provided to allow replication by others?**

Yes

**If applicable, is the statistical analysis and its interpretation appropriate?**

Not applicable

**Are all the source data underlying the results available to ensure full reproducibility?**

Yes

**Are the conclusions drawn adequately supported by the results?**

Yes

**Competing Interests:** No competing interests were disclosed.

**Reviewer Expertise:** IoT, Education, Technology Acceptance, Data Analytics

**I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.**

Author Response 26 Apr 2023

**Wee How Khoh**

We would like to express our sincerest gratitude to you and to all the reviewers for their constructive comments on our manuscript entitled "In-air Hand Gesture Signature Recognition: An iHGS Database Acquisition Protocol" and thanks for the opportunity to revise the paper. We have incorporated changes that reflect the detailed suggestions you have graciously provided. We also hope that our edits and the responses below satisfactorily address all the issues and concerns you and the reviewers have noted.

**1.** *"Some of the threshold values stated in the article should be supported by citation or justification on why that particular value is selected. For example:*

- *"Thus, to ensure validation, the collected samples that have an fps rate less than 27 are removed and re-captured again" Needs citation or justification, why 27?*
- *"The optimal hyperparameters for the polynomial kernel are tuned empirically such that the gamma ( $\gamma$ ) is set to 20, the degree of the polynomial ( $d$ ) is set to 2 and the cost ( $C$ ) is set to 1." Needs citation or justification, why the parameters were set as such?"*

**Response:**

Thank you for the comment.

We removed signature samples with a frame-per-second (fps) rate of less than 27 out of 30 in order to maintain the quality of the collected database. This decision was made after careful consideration to ensure that the database is valid and not affected by hardware constraints.

For the second point, the hyperparameters of the kernel were determined through empirical testing, and the settings we used were found which yielded optimal and stable performances across multiple experiments. Justification has been added to the manuscript.



**Revised texts:**

The hyperparameters for the polynomial kernel are tuned as such that the gamma ( $\gamma$ ) is set to 20, the degree of the polynomial ( $d$ ) is set to 2 and the cost ( $C$ ) is set to 1. These hyperparameters were determined through empirical testing, and the settings that proposed yielded optimal and stable performance across our multiple experiments were used.

*2. "The discussion of results for classification performance analysis is quite brief. Suggest to elaborate further on its impacts, for example, easy learning process and prediction stability -- easy or stable in what way? Also, apparent significance of your results compared to previous research works can be discussed in detail."*

**Response:**

To resolve the confusion of the use of the "easy learning process", we have rephrased the paragraph. This paper mainly focuses on the acquisition protocol adapted to record and collect the iHGS samples. A detailed procedure and steps of the acquisition protocol have been outlined. After thorough consideration, we decided not to include the comparison of previous research works as it has already been included in our previous research paper.

**Revised texts:**

The results found that certain vector-based features such as VBSIF-XY and VBSIF-MHIXY, possess high levels of discriminative information for classifying in-air hand gesture signatures. Compared to other methods that involve complex preprocessing, the proposed vector-based features are extracted directly from the raw data, without the need for sophisticated techniques. These features can be used directly for classification model training, such as the SVM model, making it more convenient for real-world applications. Furthermore, the small value of standard deviation associated with these features suggests a high degree of stability in predicting hand gesture signatures. This is important in any classification task, as it ensures that the classification algorithm produces consistent and reliable results across a range of input data. The stability of these features is especially valuable in applications where the quality and consistency of the input data may vary. In summary, our findings demonstrate that vector-based features, particularly VBSIF-XY and VBSIF-MHIXY, offer a robust and reliable approach to iHGS classification. These features are easy to use and require minimal preprocessing, making them ideal for real-world applications that require efficient and accurate classification algorithms.

*3. "Similar comments for the discussion of results for robustness performance analysis (refer point 2)."*

**Response:**

Thank you for your feedback. We have revised the discussion of results for robustness performance analysis.

**Revised texts:**

Distinguishing skilled forgery attacks from genuine signatures is undeniably more challenging than detecting random forgery attacks, due to the high similarity between the forgery and genuine samples. Consequently, the Equal Error Rates (EERs) for skilled forgery attacks are expected to be higher than for random forgery attacks. Our study found that the vector-based features V XY and V HOG, when adopted with the cosine distance metric,

achieved the best EER-S of 5.07% for skilled forgery attacks. This is a promising result, and it proves that these features can be effective in distinguishing skilled forgeries from genuine signatures. V BSIF-MHIXY with the Euclidean distance metric, obtained an EER-S of 9.45%, which is also a relatively good result. On the other hand, most BSIF features were found to perform poorly in verifying skilled forged hand gesture signatures, highlighting the importance of carefully selecting the features used for authentication. Similar to random forgery attacks, the Manhattan distance metric achieved the worst performance. Again, it indicates that the selection of the right distance metric is crucial for achieving good verification performance. In summary, these findings demonstrate that the verification performance of iHGS is not solely determined by the extracted features but is also highly dependent on the choice of distance metric. Therefore, careful consideration must be given to both factors in verifying the iHGS.

4. *"More update-to-date references would be good, particularly references to support the discussions of result should be of recent research works."*

**Response:**

Thank you for your comment. This paper focuses on the acquisition protocol of iHGS, which has not been widely researched in recent years, especially regarding the methodology of collecting and establishing the benchmark dataset. Therefore, we have limited our review to similar works related to hand gesture signatures and have incorporated the latest related research into the paper.

**Competing Interests:** No competing interests were disclosed.

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