Analyzing Human Observer Ability in Morphing Attack Detection—Where Do We Stand?

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Abstract—Morphing attacks are based on the technique of digitally fusing two (or more) face images into one, with the final visage resembling the contributing faces. Morphed images not only pose a challenge to Face-Recognition Systems (FRS) but also challenge experienced human observers due to high quality, postprocessing eliminating any visible artifacts, and further the printing and scanning process. Few studies have concentrated on examining how humans can recognize morphing attacks, even as several publications have examined the susceptibility of automated FRS to morphing attacks and offered morphing attack detection (MAD) approaches. MAD approaches base their decision either on a single image with no reference to compare against (Single-Image MAD (S-MAD)) or using a reference image (Differential MAD (D-MAD)). One prevalent misconception is that an examiner’s or observer’s capacity for facial morph detection depends on their subject expertise, experience, and familiarity with the issue. No works have reported the specific results of observers who regularly verify identity (ID) documents for their jobs. As human observers are involved in checking ID documents having facial images, a lapse in their competence can result in significant societal challenges. To assess the observers’ proficiency, this research first builds a new benchmark database of realistic morphing attacks from 48 different subjects, resulting in 400 morphed images. Unlike the previous works, we also capture images from Automated Border Control (ABC) gates to mimic realistic border-crossing scenarios in the D-MAD setting with 400 probe images, to study the ability of human observers to detect morphed images. A new dataset of 180 morphing images is also produced to research human capacity in the S-MAD environment. In addition to creating a new evaluation platform to conduct S-MAD and D-MAD analysis, the study employs 469 observers for D-MAD and 410 observers for S-MAD who are primarily governmental employees from more than 40 countries, along with 103 control group members who are not examiners. The analysis offers intriguing insights and highlights the lack of expertise and failure to recognize a sizable number of morphing attacks by experienced observers. Human observers tend to detect morphed images to a lower accuracy as compared to the four automated MAD algorithms evaluated in this work. The results of this study are intended to aid in the development of training programs that will prevent security failures while determining whether an image is bona fide or altered.

Index Terms—Biometrics, morphing attack detection, face recognition, human expert, ID examination, facial comparison.

I. INTRODUCTION

FACE recognition systems (FRS) are becoming increasingly common in identity management systems worldwide. A face image is mandated in all passports according to the guidelines of the International Civil Aviation Organization (ICAO), and most European nations also have national ID cards with a facial image as their main form of identification. Globally, most border controls already use automated facial recognition as the primary modality for verifying a traveler’s identity. While the practice of using live enrolment is encouraged when issuing travel and/or identity documents, many countries still allow the applicants to upload or submit a passport photo. Such a practice is vulnerable with respect to morphed or otherwise manipulated facial images.

A morphed image results from digitally combining two or more face images of two or more independent subjects, with the resulting image usually resembling all the contributing subjects. Each contributing subject to a morph can have a separate morphing factor selected by a malevolent actor. A high-quality morph can not only evade automated FRS, but can also trick a human observer (for example, a trained border officer) in both the passport application process and automatic border control, which exacerbates the situation of having two points of control compromised. While a novice attacker may create a morphed image with ghost artifacts, an expert attacker can create morphed images carefully and then process them further to eliminate all the spurious traces (morphing related artifacts in images) in image to enhance appearance. A higher-quality morph image produced by such a method typically makes it difficult for a human observer to identify the morphs [1].

While many nations only accept digital photos, some also accept printed photos that are then redigitized by the passport application officer, giving the photo the chance to be altered before printing. Such a process eliminates most subtle cues present in the morphed image in the digital domain, making it challenging to detect the morphs. Additionally, finding morphs in morphed photographs can be more difficult for human observers than detecting impostors in typical digital facial images. Addressing such concerns of operational FRS, several works have started proposing various automated approaches for detecting morphing attacks [2]. To recognize the morphed images, these morphing attack detection
(MAD) techniques often train an automated machine classifier on hand-crafted or deep features [2], [3]. While one spectrum of solutions focuses on investigating machine-driven MAD, another set of works has focused on analyzing the human observers’ ability to detect morphing attacks. We concentrate on a little- researched element of evaluating human observers’ capacity to detect the morphs, to complement the rapid development of machine-driven MAD solutions. Unlike the previous studies [1], [4], [5], we intend to study human ability on high-quality morphed images that are carefully processed in a controlled manner to eliminate artifacts. We firmly believe that by comprehending how observers perceive information during face and/or document examination, we can better develop automated face morph detection software and create the training materials required to enhance people’s capacity for face morph detection.

A. Societal and Technological Aspects

Although MAD algorithms offer a practical option to detect altered photos, most ID control systems like border control, still involve a human expert to make a judgment. A wrong decision by a human can put the security of a country and society at risk in the worst case. To prevent ethical issues, a portion of the population should not always be treated as genuine or as malicious actors. On the other hand, each choice made by an algorithm should be reviewed by a human. The clear interplay between the technology and human decision making aspects needs to be understood to avoid unjustified use of technology. We are motivated to understand and analyze the skills of trained ID control experts working in various agencies as a first step in this direction. This work is expected to serve as a foundation for creating better training programs and policies for ID control experts to avoid the negative perception and experiences of MAD technologies by understanding their strengths and limitations.

B. Contributions

In light of this interaction between society and technology, we sought to determine if ID control specialists (border officers, case handlers) (for Passport, visas, ID, etc.), document examiners - 1st line, document examiner- 2nd line, expert document examiners- 3rd line and face comparison experts (Manual examination), 3rd line) have the ability to detect morphs reliably. The details of the experts recruited and their typical employment areas are provided in Table I. The study is intended for the quantitative examination of findings from psycho-visual experiments of these expert observer groups.

We pose five critical questions to help analyze the findings as listed below:

1. How good are ID document examiners at detecting morphing attacks?
2. Are human observers with certain types of training better than others at detecting morphing attacks?
3. Does long experience working in a certain field (for instance, facial examination in ID control) positively impact MAD detection performance?
4. Are expert observers with training or experience in checking identity/identity documents better than those without training?
5. How do machine-based MAD algorithms perform compared to human observers in D-MAD and S-MAD?

We develop a new database of morphed images called the Human Observer Analysis Morphing Image Database (HOMID) as our initial contribution. The newly created database consists of images from 48 unique bona fide subjects and correspondingly 400 morphed images created by a combination of two resembling subjects (in terms of age, gender, ethnicity, and skin color) with a human expert’s intervention. Two specialists (researchers with extensive morphing experience) further postprocessed the morphed images to remove any artifacts and provided the curated set of realistic, high-quality morphed images. As an additional measure for realistic evaluation, the newly created database is supplemented with corresponding images after printing and scanning. The database also includes photographs that were taken as a probe set from an automated border control (ABC) gate in addition to morphed images. The D-MAD situation can be evaluated using the first collection, known as the HOMID-D dataset. Another set of 30 bona fide subjects from the FRGC v2 dataset [6] is further used to generate 30 morphed images. All the morphed images are further carefully postprocessed, printed, and scanned. The second subset is referred to as the HOMID-S dataset.
dataset is suitable for the S-MAD scenario and consists of 90 digital images and 90 printed-and-scanned images. To produce realistic morph attacks, both database subsets contain a good diversity of people of various ages, genders, and races (Please see Section III-A).

To facilitate the large-scale psycho-visual experiments, we also present a customized Human Observer Evaluation Platform for morph image detection. The new evaluation tool simulates a practical operational situation in which observers were given photographs to assess whether they were bona fide or morphed. Furthermore, the platform is designed following the strict guidelines of General Data Protection Regulation (GDPR) to protect and preserve participants’ privacy with full consideration to the anonymity of participants. In compliance with the university’s established ethical standards, the participants were contacted before the experiment began to obtain their consent (refer to Section III-B for details).

While the earlier works focused on analyzing human observers’ ability to detect morphing attacks, observers have been predominantly selected randomly without carefully choosing ID control experts. In this study, we use a total of 469 observers who have a specific area of expertise in face-, document-, and fingerprint-based identity verification, including border guards, passport officers, visa officers, ID experts, and forensic examiners (face, document, and fingerprints), to name a few, and compare their results to those of (100) observers who are not familiar with facial comparison or forensic examination of any kind. Such
an observer base of experts and nonexperts in our experiments also provided an insight into the role of vast experience in face comparison\(^1\) and morphed image detection, which is currently missing in the state-of-the-art studies. Table I lists the qualifications of human observers and their typical jobs. Furthermore, we contend that using human observers as a realistic benchmark can help create better training schemes for morph detection and that the knowledge gained from such a study can be applied to create more powerful machine-based MAD algorithms.

Human observers may be given just one image to decide whether a presented image is morphed in an operational scenario (for instance, passport application), or they may be given a suspected image and a reference image from a reliable source (such as ABC gate). To account for both scenarios, we study the performance of human observers under the D-MAD scenario and S-MAD. In particular, we use the images acquired from an ABC gate as a trusted source image for D-MAD human observer analysis and ask the observers to judge whether the second suspected image (unknown capture) is morphed or not using the HOMID-D subset. While in the S-MAD experiments, we employ the images from both the morphed set and bona fide set obtained from the HOMID-S dataset. As a third contribution, we compare human observer performance to machine-driven MAD algorithms to benchmark the performance of human observers against algorithms.

The key contributions of this work can therefore be listed as:

- **Human Observer Analysis Face Morph Database**: Presents a new database (HOMID) for morphed photos and ABC gate images for studying how well humans can spot morphed images. The dataset also includes images for analyzing D-MAD and S-MAD scenarios.
- **Human Observer Evaluation Platform**: A new evaluation platform mimicking the realistic operational scenario is designed where the images are provided to officers to determine if the image is bona fide or morphed.
- **Human Observer Detection Performance**: The study is based on a sizable number of observers (469 in the D-MAD trials and 410 in the S-MAD experiment) who regularly verify identification documents and/or compare biometric data to present a realistic benchmark of human observers.\(^2\) The study also benchmarks it against the novice observers with no training or experience in facial comparison or document examination to establish the benefit of domain knowledge.
- **Human Observer versus Machine Detection Performance**: To determine the advantages of each peer, a comprehensive examination of the performance of four machine-driven MAD algorithms vs human observers is presented. Two algorithms in S-MAD and two algorithms in D-MAD benchmarked in the NIST FRVT MORPH challenge [7] are evaluated on the newly constructed database.

The preliminary ideas for morph(11,12),(994,992)(11,12),(994,992)image detection and associated works on human observer analysis are presented in Section II. In Section III, Section III-A presents the details of a newly created database for human observer analysis and Section III-B presents the details on evaluation platform. Sections III-D and III-E present the details of two experiments corresponding to D-MAD and S-MAD, respectively. The findings of the human observer detection performance are presented in Section III-C together with information on the qualifications and experience of the participants along with the details on recruitment of observers. Sections III-D and III-E present the details of two different experiments in this work. Section IV discusses the key findings from the conducted analysis and Section V presents the comparison of accuracy between human observers versus algorithms for MAD. Section VI presents the summary of findings and lists the limitations before presenting the potential future directions. Section VII provides conclusive remarks on the work.

**II. BACKGROUND AND STATE OF THE ART**

A collection of linked papers that analyze human observers’ capacity for MAD are presented in this section. All representative efforts for automated morphing detection are also added to the summary.

**A. Human Observers for Face Morphing Attack Detection**

Many studies have been conducted to examine how well humans can recognize digital morph attacks. Robertson et al. [8] studied morph attack detection by human observers, in addition to a face recognition system on a smartphone. Robertson et al. [8] conducted three sets of experiments using the Glasgow Face Matching Test (GFMT) [13]. The findings of the study were based on 19 female and 30 male observers.

The initial face image of each individual was cropped (to remove the torso) and pasted onto a white background that measured 14\,cm\,×\,10.5\,cm for the experimental setup. The second image was embedded in a frame similar to a U.K. passport (same size). Each combination of subjects resulted in the creation of five morphed images, with morphing factors starting at 90\% from the first subject and 10\% from the second subject and a step size of 20\%. In Experiment-1, the observers were asked to confirm whether the images were mated images for the shown trusted image and the second nontrusted image without the prior knowledge of manipulations.

Images of the same person or a modified image were used to randomize the tests. Each trial had two images, and the observer had to choose whether the shown images were the same person or not. Each participant in this experiment underwent 49 trials, with 35 morphed pair trials, 7 mated comparison trials, 7 nonmated comparison trials, and 49 randomly chosen trials from the image collection. 25 female and three male observers participated in this experiment where the false

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1\(^\text{Face comparison in this context refers to comparing two face images to make a decision on mated or non-mated pair of subjects.}\)

2\(^\text{A total of 790 observers have participated in the experiments in different categories. However, we only consider the observers who have completed the experiments to conduct the analysis in analyze this work.}\)
The observers were provided with an introduction to face morphing, morphing attacks, and hints to identify the morphed images. The observers were required to complete 15 trials, each of which contained 10 morphing face photos and 5 real face photographs. The observer had to first contrast the face image from the passport with the genuine or altered image that had been provided. The second experiment was for face comparison, with 25 trials (10 mated comparisons, 5 nonmated comparisons, and 10 morphing comparison trials). Two images were shown to observers one on a frame from a model passport to be contrasted with a brief video clip in which the traveler rotated his or her head. Finally, the observer had to decide on the passport face image, to decide if the traveler’s image was morphed or not looking at the video.

In both trials, 189 observers took part, and 21 of them had never seen a face transform before. In the first experiment (no reference), unskilled observers’ true positive rate (TPR) was reported to be 65.65%, and a TPR of 63.33% for skilled observers. The TPR of competent and untrained observers in the second experiment (a face comparison) were reported as 93.45% and 95.25%, respectively. Makrushin et al. [10] claimed that training the unskilled observers would increase the detection ability to reach the performance of skilled observers. The accuracy of a face-recognition program from Dermalog Face Recognition [17], [18] was also investigated by Makrushin et al. [10] where they noted the false acceptance rate (FAR) of human observers was greater (15.45%) than the algorithms’s (0%).

A pair of 54 digital images was used in the Nightingale et al. [12] investigation of a human observer’s capacity to recognize altered images under S-MAD and D-MAD conditions. However, the study employed one hundred workers on Amazon’s Mechanical Turk (AMT) in a crowd-based approach who were neither expert examiners nor observers familiar with face recognition. While the observer’s accuracy in distinguishing between genuine and fake images was 80.8%, their success rate in detecting morphing was only 58.3%. However, the observers who received some training obtained a similar accuracy of 59.2%, but the work noted that participants made different mistakes as compared to the original experiment. Further testing of the face-recognition algorithm by Nightingale et al. [12] revealed very poor performance in an Area Under the Curve (AUC) of 0.38.

Zhang et al. [11] investigated the capacity of human observers using 42 inexperienced viewers and 14 experienced observers using 15 genuine and 75 morphed photos. The experienced observers were extremely familiar with morphing and included ID experts in border control. Unlike the previous works, Zhang et al. [11] studied five different types of morphing algorithms that included landmark-based morphs and Generative Adversarial Network (GAN) based morphs. The detection accuracy for the skilled group was 97.14%. While detecting landmark-based morphs was difficult compared to detecting GAN-based morphing, the inexperienced obtained an accuracy of 79.21%. Five experienced observers and ten novice observers were used in Zhang et al.’s [11] study of D-MAD detection abilities. The group with relevant expertise had an overall accuracy of 86%. 

In 2016, Ferrara et al. [14] studied face morph attack detection with both human observers and algorithms. Using the free GIMP Animation Package v2.6 [15] and the GIMP Animation Package v2.8 (GAP) [16] software, 80 face morphs were produced. The observers were instructed to report whether the morphing photographs matched against a trusted bona fide (i.e., original) face image in each trial, which included two face images. In this experiment, there were 543 nonexpert observers and Forty-four experts (border guards). The results showed that morphed images were not correctly detected (i.e., classified as a bona fide image).

In four studies akin to those conducted by Robertson et al. [8], Kramer et al. [9] investigated human and algorithmic morph detection performance while utilizing a high-quality morph database. Overall morph detection accuracy of experts (56%) was higher than nonexperts (52.2%) as analyzed using signal detection measures. There was no discernible performance gain in morph detection following the morph detection training session. Further, single image-based morphing attack detection (S-MAD) was studied using 120 images and 40 participants (border guards). The results showed that morphed images were not correctly detected (i.e., classified as a bona fide image).

Ferrara et al. [1] studied face morph attacks under automated border control (ABC) gate settings. It was discovered that all 18 altered photographs were not recognized as being morphed by qualified face comparison experts. Makrushin et al. [10] conducted a Web-based simulation of a border control scenario.
A detailed analysis of all the existing state-of-the-art for human observer analyses for MAD is presented in Table II.

### B. Algorithms for Morphing Attack Detection

1) **Differential Morphing Attack Detection (D-MAD):** In the lines of human observer-based morphing attack detection, several approaches have been devised for automated morphing attack detection. The second suspicious image is examined to determine if it has been morphed or not using a trustworthy live capture image from an ABC gate or other reliable capture device. The first approach of D-MAD was based on inverting the morphing process in a reverse-engineered manner, which was termed Demorphing [19]. Similar to this, several studies have been published in which the difference between the feature vectors of the genuine and morphed images are utilized to assess whether an image is genuine or morphed [20], [21]. Morphing attacks were also detected using features from the 3D shape and the diffuse reflectance component estimated directly from the image in [21], and the deep features from two different networks were used to determine the difference in features [20]. Another group of works investigated morphing by examining the change in landmarks of genuine and suspected morph images in the region of the face [22], [23].

2) **Single Image Morphing Attack Detection (S-MAD):** S-MAD algorithms largely rely on learning a classifier to distinguish the bona fide image from a morphed image. The texture data is extracted from the normalized and aligned face of a suspected morph image. The texture features such as Binarized Statistical Independent Features (BSIF) and Local Binary Patterns (LBP) are used to classify the images using a pretrained Support Vector Machine (SVM) classifier [23], [24], [25], [26], [27] in the earlier works. While extending the works for MAD, another approach was proposed to exploit the color spaces and the scale spaces jointly [24], [28]. Pretrained deep networks for texture feature extraction were used to detect the morphing attacks not only in the digital domain but also in the redigitized domain (after a print-scan transformation) [29] to address and detect the postprocessed morphed images. Notably, the earlier works have employed two deep neural networks; including VGG19 [30] and AlexNet [31], where they perform a feature-level fusion of the first fully connected layers [29]. Other deep networks have been researched for morph attack detection in an ongoing effort [32]. Another approach to detecting morphing attacks was proposed by extracting the features from the “Photo Response Non Uniformity (PRNU),” where the characteristics...
of the image sensor were employed to determine if the image was morphed or not [33]. Better performing algorithms have been reported, including dedicated context aggregation networks to automatically model noise [34] using color spaces to seek residuals of the morphing process.

C. Limitations of the Existing Works

With a detailed review of the existing state-of-the-art in previous section, we note a set of limitations in the existing works in this section.

- The majority of the previously mentioned works were primarily concerned with D-MAD or S-MAD settings. As a result, they do not accurately benchmark the ability of the same human observer to evaluate the altered images in D-MAD and S-MAD situations.
- Furthermore, the morphed images utilized in those studies were not carefully postprocessed to mimic the authentic passport images on ID cards, which resulted in a somewhat skewed conclusion. For instance, Kramer et al. [9] used a high-quality morphed database, but the images themselves do not have a realistic background for face images. Without a neck or other human face background, only the cropped face is shown. Another set of works [8], [14] directly use the morphed image, without any modification/postprocessing despite many visible artifacts leading to biased observations and thereby conclusions.
- The majority of earlier studies on morphing detection using human observers used a smaller collection of images. However, the small size of the dataset does not lead to a statistically conclusive result. The reported works employ a small set of expert observers to validate the initial observations made by the previous studies. To obtain precise results in subjective studies, Brysbaert [35] has discussed the significance of the sample size and number of participants. The large sample size experiment gives a more precise statistical analysis.

We perform empirical research depending on the information acquired from human observers to address the constraints of the current state-of-the-art and respond to the research questions listed previously.

III. METHODOLOGY

Our methodology consists of three main parts, which are as follows: the development of new datasets; the building of an evaluation platform to collect data on human observers; and the data collecting related to the evaluation and analysis of the human observers. We first present the analysis at a high level for detecting D-MAD and S-MAD, following which various subanalysis is presented measuring the performance with respect to duration of the training, field of expertise, and detection ability in the print-scan setting. Additionally, we provide a thorough examination of the detection accuracy for S-MAD and D-MAD using two alternative automated techniques.

A. Datasets: Human Observer Analysis Morphing Image Database (HOMID)

We first create a new database called the HOMID to address the lack of face images for human observer analysis of morphing attack detection. As a noted limitation in the earlier works, the face images employed for the human observer analysis do not have images respecting the ICAO standards for Machine Readable Travel Documents (MRTD) [36]. As a result, we develop a new database that complies with ICAO criteria while still being realistic. There are two primary subsets of the database, each including bona fide and morph subsets. The first subset, HOMID-D, corresponds to D-MAD settings where the bona fide images are captured from a regular photo studio setting, and bona fide probe images are captured from a real ABC gate. The process described later is used to create the morphed photos in this subgroup. The second subset corresponds to S-MAD settings where the bona fide images are captured from a real photo studio setting, and bona fide probe images are captured from a real ABC gate. The process described later is used to create the morphed photos in this subgroup. The second subset corresponds to S-MAD settings where the bona fide images are captured from a real photo studio setting, and morphed images are created, as explained further below. To explore all the facets of MAD by human observers, both subsets of data have printed-scanned photos that have undergone digital postprocessing.

1) HOMID Differential MAD Subset: We produce the first subset of data that contains genuine and morphed images to explore how well human observers can recognize morphing in a differential (i.e., reference-based) environment. The bona fide images are collected from 48 unique subjects with different age groups, gender, and ethnicity. The demographic distribution of the dataset is provided in Table IV.

HOMID-D Bona fide Subset: To replicate the ICAO passport photo, the face images were taken in a photo studio with adequate lighting, no shadows, no poses, and neutral expressions on a white background. The face image of each data subject was captured multiple times, from which one image was chosen for creating morphs, and other images were used
TABLE IV
DEMOGRAPHIC DISTRIBUTION OF HOMID-D SUBSET FOR BONA FIDE IMAGES

| Ethnicity   | Caucasian | South Asian | Middle East | Chinese |
|-------------|-----------|-------------|-------------|---------|
| Female      | 2         | 2           | 3           | 0       |
| Male        | 26        | 10          | 2           | 3       |
| Total       | 28        | 12          | 5           | 3       |

Fig. 2. Bona fide subset in HOMID-D.

for studying the vulnerability of FRS. Each photo was taken at a high resolution and afterward reduced to a 413x513 pixels size. Further, the cropped face images in the bona fide set were carefully cropped to respect the minimum Inter-Eye Distance according to passport image standards in various countries. There are 480 total photos in the genuine subset. Figure 2 offers an example representation of the genuine photos in the HOMID-D subset.

**HOMID-D Trusted Capture Subset:** In the D-MAD setting, a trusted live capture image is compared against a suspect image. We use an ABC gate to build a series of probe pictures that correspond to trusted capture conditions. Images from each of the 48 subjects were captured using the ABC gate resulting in 10 different attempts., five of the 10 photos were utilized to evaluate the vulnerability of supplied morphs. Specifically, we have employed a state-of-art Commercial-Off-The-Shelf (COTS) system to verify the quality of the morphed images against the captured ABC gate images. The good quality of the produced morph pictures and postprocessing quality is confirmed by the high comparative score. The rest of the 5 images from each subject were further scrutinized for appearance and quality scores by an expert researcher based on which the best image was chosen for subjective experiments. Figure 3 shows a selection of photographs from our database that correlate to the real images seen in Figure 2.

**HOMID-D Morph Subset:** We combine two similar subjects to generate 400 morphed images using the newly created photographs of 48 real subjects (in terms of age, gender, ethnicity, and skin color). Based on the earlier works indicating high attack strength of morphed images with a morphing factor of 0.5 [1], [2], [3], [14] (i.e., 50% contribution from each subject), we create the morphed images using a morphing factor of 0.5. To prevent the creation of implausible morphing combinations, the subjects for morphing were chosen by a human expert. Further, to create highly realistic morphed images to challenge the human observers, each of the morphed images was postprocessed to eliminate any artifacts in the image signal stemming from the morphing process, such as double contours in the iris region, incorrect lip region, etc. Two specialists also examined each postprocessed image to ensure the excellent quality of created morphed images produced. A sample illustration of a postprocessed image is provided in Figure 4 where one can observe the naive morph generation resulting in visible artifacts in the iris and nose areas while the postprocessed image eliminates such artifacts, resulting in a realistic face image.

Additionally, since providing a printed image that is afterward scanned is a standard procedure in many nations, we created another subset of morphed photographs by printing and scanning them with an Epson Expression Premium XP-7100 [37] photo printer. Thus the morphed image set has a total of 400 digital images and 400 printed-scanned images, both after postprocessing.

2) HOMID Single Image MAD Subset: While decisions about whether an image is genuine or a morph can be made based on an image pair in some application settings, such as border control (e.g., with trusted image capture), other scenarios, like visa or passport applications, just have one image without any reference images. For instance, applying for a Bl USA visa needs the applicant to upload the passport image, and this could potentially be a morphed image on which the decision has to be made. To study the human observer performance for MAD in such scenarios, we create a Single-Image Morphing Attack dataset, which we refer to as the HOMID-S dataset. The HOMID-S subset has bona fide and morphed image subsets, similar to HOMID-D subset, as discussed below. In addition, to consider image capture conditions other than our dataset, we make use of the FRGC v2 dataset [6] to derive HOMID S-MAD dataset as explained further.

**HOMID-S Bona fide Subset:** We selected 30 subjects (15 men and 15 women) from the FRGC v2 dataset [6] to
produce a dataset of bona fide images. As the FRGC v2 dataset provides multiple captures for each subject, we choose a high-quality enrolment image for the bona fide set and further process each image to conform to ICAO standards for the face image. The selected bona fide subset has been carefully checked to make sure that any rotations or poses are corrected. The demographic distribution of the chosen subjects is provided in Table V.

**HOMID-S Morph Subset:** We further generate morphed images for the chosen 30 subjects using a morphing factor of 0.5. To produce realistic morphed photos, each subject is merged with another subject that closely resembles it in terms of age, gender, and race. Further, to assure high-quality morphed images, we carry out manual postprocessing with human expert intervention. We consequently produced 15 morphed images for male individuals and 15 morphed images for female subjects. Each of the morphed images, which are post-processed, are also printed and scanned in the lines of previous works [2], [3], [24], using an Epson Expression Premium XP-7100 [37] photo printer. A sample illustration of the images in the HOMID-S subset is provided in Figure 5, which depicts both bona fide and printed-and-scanned images.

**TABLE V**

|                | Digital Bona fide | Digital Morph | Post-processed Bona fide | Post-processed Morph | Digital Bona fide | Digital Morph | Post-processed Bona fide | Post-processed Morph |
|----------------|-------------------|---------------|--------------------------|----------------------|-------------------|---------------|--------------------------|----------------------|
| Male           | 15                | 15            | 15                       | 15                   | 15                | 15            | 15                       | 15                   |
| Female         | 15                | 15            | 15                       | 15                   | 15                | 15            | 15                       | 15                   |
| Total          | 30                | 30            | 30                       | 30                   | 30                | 30            | 30                       | 30                   |

**B. Platform:** iMARS Human Observer Platform for Evaluation - iHOPE

We also developed an individualized Human Observer Platform for Evaluation (iHOPE) for morphing image identification to support large-scale trials. The new evaluation platform mimics the realistic operational scenario where the images are provided to observers to determine if the image is bona fide or morphed. Additionally, the platform was created under the tight restrictions of the GDPR to safeguard participants’ privacy while giving full regard to participants’ anonymity.

Currently, the platform supports two sets of experiments that correspond to the D-MAD and S-MAD scenarios. These experiments can be carried out on a desktop environment that is modeled after the methods currently used in operational settings. The participants first need to register their details by providing their email address (voluntary), name, age, and gender. On the homepage, there is a summary of the experiment’s objectives for each participant. Moreover, each participant was asked to indicate whether they had any training in facial comparison, document examination and morphing, the length of said training, and their line of work. The platform first takes users to the D-MAD experiment, where they may view their results and learn how much time they spent on each task. Then, the platform presents a pair of images of a chosen subject by providing the trusted capture image (captured from an ABC gate) and an unknown-capture image. The unknown-capture image is chosen at random from either a morphing set or a bona fide set of the relevant subject, whereas the trusted capture image is genuine. All the observers are presented with the same pairs in D-MAD experiments to derive the conclusions in this work. Each participant sees the photos on the platform in a different order at random. The platform is also designed to collect meta-data on how much time the participants spend on each image pair. By providing the morphed images, bona fide images, and trusted capture (ABC gate) images with the same clothes in both images for each pair of photographs, care is taken to avoid any decision bias caused by the clothing worn in the given images. Figure 6a illustrates the designed iHOPE-D-MAD evaluation page.

Considering various operational practices, the platform also allows the participants to zoom in and enlarge the images before making a decision. The platform also enables the participants to take a break and resume the experiments as needed, which lessens the strain on their minds during lengthy cognitive experiments. The total score is shown in the D-MAD experiments every time the participant clicks on “Continue later.” Once the D-MAD experiment is over, the platform then refers users to the S-MAD experiment. Figure 6a presents the iHOPE S-MAD evaluation platform where the participant is presented with one image from an unknown-capture setting of a subject. The subgroups of bona fide and morphed images from which the photographs are drawn are presented at random.

**C. Participants/Observers:** iMARS Human Observer Evaluation

The online evaluation platform uses two alternative configurations, called D-MAD and S-MAD, to compare how well humans are at spotting morphed images. The platform was designed to allow the participants to pause and resume the experiment at their own pace to accommodate busy schedules, and to avoid fatigue and cognitive load in making decisions for the experiment.

a) **Recruitment of Observers:** The observers were recruited from national organizations that regularly deal with ID management and verification. Invitations were sent through secure channels through liaisons at various agencies to create an observer pool of Border Guards (30), Case handlers - Passport, visas, ID, etc (150), Document examiners - 1st line (38), Document examiners - 2nd line (40), Document examiners - 3rd line (30), Face comparison experts - Manual...
examination (44), ID Experts (53) and Others (84). The experiment’s objectives were explained to the observers in a brief introduction and set of instructions. The participants were asked for explicit consent according to the national guidelines and GDPR. In addition to obtaining consent, a questionnaire was used to record participant’s demographics, employment history, and training duration for our study. Further, each participant was given a unique code to anonymize the participant information, which could also be used to get the data deleted if the participant did not wish to allow his/her data to be used for analysis.

The participants were asked to provide the following information in the questionnaire:
- Age, gender, email address and nationality
- Profession/Line of work
  - Experience with facial examination (< 6 months, 6-12 months, 1-3 years, 3-5 years and more than 5 years)
  - Experience document examination (< 6 months, 6-12 months, 1-3 years, 3-5 years and more than 5 years)
  - Is the participant a documented super recognizer⁴
  - Experience in morphing attack detection (Half a day, Half-day to one day, 2-3 days, 4-5 days, more than 5 days)
  - Line of work (Face comparison, Fingerprint expert, Document examiner (1st, 2nd and 3rd line), ID Expert (Embassy, Police and other government authorities), Case handler (ID, Visa, Passport), Border guard (1st line, 2nd line))

D. Experiment-I: D-MAD Human Observer Evaluation

In this study’s 400 image comparison trials, two face photos were displayed side by side as illustrated in Figure 6a. Each trial was randomized by choosing the image pairs randomly.

⁴Super recognizers are facial examiners who perform with very high levels of accuracy on face recognition tests [54], [55].

| Comparison                          | Digital images | Print and scanned |
|-------------------------------------|----------------|------------------|
| Morph vs Bona fide                  | 48             | 48               |
| Morph vs ABC gate image             | 48             | 48               |
| Post processed morph vs Bona fide   | 48             | 48               |
| Post processed morph vs ABC gate image | 48         | 48               |
| Bona fide vs Bona fide              | *16            | 0                |
| Total                               | 208            | 192              |

* indicates the total trials to check the consistency of the participants.

Four hundred trials were divided into four parts, where each part consisted of 100 unique comparisons. Participants were asked to determine if the second image, which was assumed to be from an unreliable capture, was a “bona fide” or “morphed image” after viewing the first image from a trusted live capture. An optional zoom-in function was provided on the platform for participants who wished to enlarge the images before deciding, mimicking the real-life deployment solution. After 100 comparisons, the acquired accuracy was frequently displayed to encourage the participants.

The D-MAD experiment consisted of 48 comparison trials in 5 different categories as listed in Table VI and the distribution of images in the trial are provided in Table III. The evaluation added eight random bona fide v/s bona fide comparisons in addition to the identification of morphing images to conduct a consistency check on whether a user was arbitrarily selecting the same image repeatedly or if the clicks were random. The final analysis has removed all such data where a random click behavior was observed.

E. Experiment-II: S-MAD Human Observer Evaluation

In the S-MAD human observer evaluation, a total of 180 individual images were presented to each observer. The participants were only given one image, as shown in Figure 6b.
and were required to decide whether it was a genuine photograph or a morphed image. The face images displayed in the evaluation platform were rescaled to EU passport image standards (413x531 pixels and JPEG2000 compression) [38]. The participants had access to a zoom feature that enlarges the image to fill the entire screen as they analyze how a border officer or examiner might conduct a comparable operation in real life. The participants further received the final scores after the completion of 180 trials and intermediate scores after 90 trials.

IV. FINDINGS, ANALYSIS AND DISCUSSION

This section covers the results of the tests and offers a thorough analysis of the patterns seen in the evaluation of human observers. The analysis is based on 469 observers in the D-MAD experiment and 410 observers in the S-MAD experiment. The distribution of different lines of work is presented in Table VII in D-MAD and S-MAD experiments. For the reader’s benefit, we also provide a thorough discussion of each subgroup of findings.

A. Metrics for Evaluations

To show the results, we use Attack Presentation Classification Error Rate (APCER) and Bona fide Presentation Classification Error Rate (BPCER). APCER is defined as the proportion of attacks classified as bona fide and BPCER is the proportion of bona fide images classified as attacks. The accuracy is reported as an average of Attack Presentation Classification Error Rate (APCER) and Bona fide Classification Error Rate (BPCER) aligning the results to the NIST FRVT MORPH challenge [7]\(^5\) and is defined as below:

\[
\text{Accuracy} = \frac{1 - \text{APCER} + (1 - \text{BPCER})}{2}
\]

\(^5\)The NIST FRVT MORPH report is based on the continuous MAD scores in the scale of 0-1, which allow computation of the BPCER at given thresholds of APCER (for instance, BPCER@APCER=0.1%). In our case, human observers make a binary decision and thereby we refrain from computing the BPCER at any thresholds of APCER.

B. Overall Accuracy in D-MAD and S-MAD

We first present the overall detection accuracy for D-MAD and S-MAD, before analyzing each individually. Figure 7 shows that while few observers have more than 95% accuracy, the average accuracy of identifying the morphing attack in the D-MAD condition is 64.10% \((\text{min} = 19.75\%, \text{max} = 99.50\%, \text{SD} = 17.71\%, \text{Mdn} = 62.75\%)\). We note a slightly lower average accuracy in the S-MAD setting corresponding to 58.98% \((\text{min} = 33.33\%, \text{max} = 85\%, \text{SD} = 9.75\%, \text{Mdn} = 59.44\%)\). Unlike the D-MAD setting, we note that none of the observers has more than 82% detection accuracy in S-MAD and this can be attributed to the challenging decision-making process in the absence of a reference image. We analyze and present several factors in the following subsections based on these observations.

C. Training in Facial Comparison v/s MAD

Since facial examination expert viewers are considered to be skilled in facial comparison, we predicted that factors like the amount of time spent on topic-specific training and the amount of facial examination experience a person has will affect how accurately they detect face morphs. Therefore, we analyze the MAD accuracy of human observers for both D-MAD and S-MAD experiments. We specifically, group the observers into six groups based on the length of training they have received:

| Line of work | Number of participants | Average Accuracy | Number of participants | Average Accuracy |
|--------------|------------------------|-----------------|------------------------|-----------------|
| Border Guard | 30                     | 64.66           | 26                     | 55.17           |
| Case handler- Passport, visas, ID, etc | 150                   | 63.45           | 137                    | 56.65           |
| Document examiner- 1st line | 38                     | 60.79           | 30                     | 57.63           |
| Document examiner- 2st line | 40                     | 68.64           | 34                     | 62.56           |
| Document examiner- 3rd line | 30                     | 65.74           | 25                     | 61.51           |
| Face comparison expert (Manual examination) | 44                     | 72.56           | 39                     | 64.63           |
| ID Expert | 53                     | 63.09           | 50                     | 57.21           |
| Other | 84                     | 64.66           | 69                     | 55.17           |
| Student | 103                    | 56.91           | -                      | -               |
| Total participants | 572                    |                 | 410                    |                 |
| Experts | 469                    |                 | 410                    |                 |

Fig. 7. Overall accuracy of morphed image detection for D-MAD and S-MAD experiments.
no prior experience, less than 6 months, 6–12 months, 1–3 years, 3–5 years, and more than 5 years. We make the following observations from the results obtained:

1) Results for Experiment-I - D-MAD:
- The observers with no specific training on face comparison obtain a MAD accuracy of 62.81% (min = 19.75%, max = 98.50%, SD = 17.69%, Mdn = 61.50%). In contrast, experienced observers in D-MAD settings, as shown in Figure 8a, achieve an average accuracy of 64.89% (averaged over five different experience groups, (min = 23.75%, max = 99.50%, SD = 17.71%, Mdn = 63.37%).
- We use the Kruskal–Wallis test to assess how different observers with various levels of facial examination training detect morphing attacks. The test revealed no significant differences (H(5) = 7.85, p = 0.167) across the groups (n = 173, 74, 30, 77, 44, 71).
- We further investigate if longer training length in facial examination helps in detecting morphing attacks and we conduct another Kruskal–Wallis test. The test found no significant differences between the groups (Less than 1-year training = 277, More than 1-year training = 192) (H(1) = 1.01, p = 0.315). And a similar observation is also made for observers with more than 5 years of training to those with fewer than 5 years, no discernible changes were found (H(1) = 2.39, p = 0.122, Less than 5 years = 350, More than 5 years = 60).

2) Results for Experiment-II - S-MAD:
- The average MAD accuracy with respect to facial examination training in the S-MAD setting is 59.77% (averaged over five different length categories, (min = 36.11%, max = 80.56%, SD = 9.89%, Mdn = 60.50%).). At the same time, observers with no experience had an accuracy of 57.98% (min = 33.33%, max = 85%, SD = 10.70%, Mdn = 57.78%) as presented in Figure 8b.
- Observations for different training lengths for facial examination in the S-MAD setting indicated no significant differences (H(5) = 13.63, p = 0.018) across the groups (n = 155, 62, 27, 65, 41, 60) with no training to more than 5 years of training. No significant differences (H(1) = 0.88, p = 0.348) across the groups (Less than 1-year training = 244, More than 1-year training = 166) were further observed and in similar lines, when comparing observers with more than 5 years of training to those with fewer than 5 years, no discernible changes were found (H(1) = 2.39, p = 0.122, Less than 5 years = 350, More than 5 years = 60).

3) Common Observations: The participants (74 in D-MAD and 62 in S-MAD) with less than 6 months of training in face comparison (62.52% in D-MAD, 61.53% in S-MAD) showed no significant differences among the different observers to observers with 6–12 months of training (67.59% in D-MAD, 62.53% in S-MAD). However, the observers with 6–12 months of training performed best in both categories. Our observation indicates that training in facial comparison does not necessarily lead to better MAD. As far as we are aware, there is currently no comprehensive training program for MAD by humans. Generally, MAD is just one part of document examination training or face comparison training.

D. Experience in Document Examination v/s MAD

We also evaluate the impact of the experience of document examiners on the accuracy of detecting the morphed images. We divide the document examiners into six groups based on the length of their training specifically in document examination, no prior experience, less than 6 months, 6–12 months, 1–3 years, 3–5 years, and more than 5 years. We make the following observations from the results obtained.
Fig. 9. Impact of training in document examination on MAD accuracy of human observers.

1) Results for Experiment-I - D-MAD:
- The observers with specific training on document examination reached an average accuracy of 65.12% in D-MAD (258 participants, min = 19.75%, max = 98.50%, SD = 16.51%, Mdn = 62.25%). Comparatively, the untrained observers had an average accuracy of 59.27% (186 participants, min = 65.05%, max = 99.50%, SD = 23.75%, Mdn = 63.50%).
- The observers with less than 6 months (43 participants) and 6–12 months (22 participants) training in document examination obtained a better average accuracy of 65.31% and 68.12% in the D-MAD setting. However, the average accuracy of all the observers with training is 63.95%, as noted in Figure 9a.
- We use the Kruskal–Wallis test, as described in the preceding section [39], to assess the variations in MAD across observers with varying training lengths in document analysis. The test revealed no significant differences ($H(5) = 5.23, p = 0.388$) across the groups ($n = 211, 43, 22, 66, 45, 82$) with no training to more than 5 years of training, refer to Figure 9a.
- Further research into whether longer training durations in document examination aid in the detection of morphing attacks found no appreciable changes ($H(1) = 1.94, p = 0.164$) across the groups (Less than 1 year training = 254, More than 1 year training = 193). Additionally, a similar finding was made with observation with more than 5 years of training with an $H(5) = 0.02, p = 0.879$ (Less than 5 years = 387, More than 5 years = 82) using the Kruskal–Wallis test.

2) Results for Experiment-II - S-MAD:
- We note a drop in average accuracy in the S-MAD setting for observers with no prior training (186 participants) in document examination with an accuracy of 59.27% compared to 65.12% in the D-MAD setting. The decrease in accuracy highlights how difficult the S-MAD setting is when there is no reference image to compare it against.
- The observation for the S-MAD setting where no significant variations were seen among groups of observers with various training lengths in document evaluation with a similar methodology to D-MAD ($H(5) = 6.61, p = 0.250, n = 191, 36, 20, 55, 41, 67$) with no training to more than 5 years of training as shown in Figure 9b. No significant differences were further observed for groups with less than 1 year training ($n = 56$) and more than 1 year training ($n = 163$) where ($H(1) = 3.79, p = 0.051$). In a similar manner, no discernible variations were found between observers with more than 5 years of training and those with less than 5.

3) Common Observations:
- Similar to the D-MAD setting, the accuracy of observers with 6–12 months (20 participants) training in document examination obtain a higher average accuracy of 65.31% and 68.12% in the D-MAD setting. However, the average accuracy of all the observers with training is 63.95%, as noted in Figure 9a.
- The accuracy of observers with 6–12 months (20 participants) training in document examination obtained an accuracy of 59.27% compared to 65.12% in the D-MAD setting. The decrease in accuracy highlights how difficult the S-MAD setting is when there is no reference image to compare it against.
- The observation for the S-MAD setting where no significant variations were seen among groups of observers with various training lengths in document evaluation with a similar methodology to D-MAD ($H(5) = 6.61, p = 0.250, n = 191, 36, 20, 55, 41, 67$) with no training to more than 5 years of training as shown in Figure 9b. No significant differences were further observed for groups with less than 1 year training ($n = 56$) and more than 1 year training ($n = 163$) where ($H(1) = 3.79, p = 0.051$). In a similar manner, no discernible variations were found between observers with more than 5 years of training and those with less than 5.

E. Line of Work v/s MAD Accuracy

Additionally, we examine the categories of border guards and case handlers to determine the accuracy of MAD based on
the line of work (for Passport, visas, ID, etc.), document examiners - 1st line, document examiner- 2nd line, expert document examiners- 3rd line, face comparison experts (Manual examination), 3rd line, ID experts and miscellaneous as another category. According to their area of work, Figure 10a and Figure 10b show the accuracy of human observers. Below are some observations we made as a result of these analyses.

1) Results for Experiment-I - D-MAD:
- The observers who work on face comparison (manual examination) have the highest average accuracy of 72.56% (44 participants, \( \text{min} = 23.75\% \), \( \text{max} = 99.50\% \), \( \text{SD} = 20.97\% \), \( \text{Mdn} = 77.25\% \)), with 12 participants obtaining more than 90% accuracy in the D-MAD setting.
- While a high accuracy is noted for case handlers of passports, visas, and ID with 11 participants obtaining more than 90% accuracy, 26% of participants (a total of 150 participants) obtain less than 50% accuracy in detecting morphs in the D-MAD setting.
- Additionally, it should be mentioned that the border patrol agents have respectable accuracy, despite a tiny percentage of them being unable to identify the morphs in the D-MAD setting.
- It should be observed that various observers outside of a specific field of expertise who match face comparison specialists in morph detection in the D-MAD settings, while the average performance drops in this group in S-MAD settings.

2) Results for Experiment-II - S-MAD:
- In contrast to D-MAD, the accuracy is significantly lower in the S-MAD setting for border guards.
- Similar to the last set of analyses, the average accuracy decreases in the S-MAD scenario when no reference photos are available, independent of the lines of work.

3) Common Observations: Special consideration should also be given to various observers outside of a specific field of expertise who match face comparison specialists in morph detection in the D-MAD settings, while the average performance drops in this group in S-MAD settings.

We further conduct a statistical analysis utilizing a different field of study and, due to the variable number of observers, we utilize ranks in one-criterion variance analysis [39] since we are motivated by small distinctions. With the given number of observers in each different line of work corresponding to Figure 10a (n = 30, 150, 38, 40, 30, 44, 53), we note the \( H(6) = 18.99, p = 0.004 \) indicating significance between the observers in a different line of work. However, in contrast to observers in other fields, experts in face comparison (Manual examination), we note an \( H(1) = 10.53, p = 0.001 \) suggesting the better performance of face comparison experts.

F. MAD for Digital v/s Print-Scan Images

We note the difficulty of the MAD job for digital and printed-scanned photos, which relate to a real-life setting, in addition to the analysis that was previously provided. While the former is common in applying for visas by uploading digital images, the latter can also be observed in different countries where the printed-scanned images can be uploaded to obtain valid ID documents. This series of analyses compare the accuracy of digital versus printed-scanned morphed images, as seen in Figure 11.

1) Results for Experiment-I - D-MAD:
- It can be noted that the observers spot the morphed images in the digital domain with an average accuracy of 64.22% (\( \text{min} = 42.05\% \), \( \text{max} = 95.73\% \), \( \text{SD} = 20.97\% \), \( \text{Mdn} = 77.25\% \)) in D-MAD settings. In contrast, the accuracy drops slightly for printed-scanned images to 63.39% (\( \text{min} = 38.80\% \), \( \text{max} = 94.40\% \), \( \text{SD} = 10.55\% \), \( \text{Mdn} = 64.41\% \)). To further comprehend whether the detection accuracy for digital and print-scan attacks differs statistically, we conduct Levene’s test [40] by performing ANOVA on the absolute deviations of the data values from their group means and we note a \( t(1.93) = 7.26, p = 0.007 \). The analysis indicates no discernible difference between observers in identifying either category (\( p > .001 \)).

2) Results for Experiment-II - S-MAD:
- However, the average accuracy drops to 59.18% (\( \text{min} = 32.22\% \), \( \text{max} = 88.88\% \), \( \text{SD} = 11.70\% \), \( \text{Mdn} = 58.88\% \)) and 58.78% (\( \text{min} = 32.22\% \), \( \text{max} = 81.11\% \), \( \text{SD} = 9.05\% \), \( \text{Mdn} = 60\% \)) for digital and printed-scanned images, respectively, in S-MAD settings. It should be observed that no observer exceeds an accuracy of 90% in the S-MAD setting, highlighting the difficulty
in identifying altered images in the absence of a reference image. The lower quality of images in S-MAD can be a factor for lower accuracy. Further analysis is needed to understand the drop in accuracy for both S-MAD and digital v/s printed-scanned images.

G. MAD v/s Demographics of Observers

To see whether these traits contribute to improved MAD accuracy, we also examine the demographics of the observers. Specifically, we look at age, gender, and country of work (not ethnicity) for S-MAD and D-MAD. Figure 12 presents the correlation of MAD versus the age of the observers.

1) Results for Experiment-I - D-MAD: As noted in Figure 12a and Figure 12b, there appears to be no strong correlation between the age of observers and MAD accuracy.

2) Results for Experiment-II - S-MAD: It is simple to see the general trend of decreased MAD accuracy in S-MAD settings compared to D-MAD settings by comparing Figure 12b to Figure 12a. The absence of an image pair with a trusted live capture as a reference makes it a challenge to determine if a suspected image is morphed or not.

Since the majority of the observers are from European nations, we do not come to any firm conclusions even if we also analyze the detection accuracy in terms of nationality. Also, no significant differences were observed concerning gender.

H. Improvement of Detection Accuracy Over the Number of Images

Taking into account the low accuracy of the various groups of observers in identifying morphing attacks in both D-MAD and S-MAD situations we also analyze if the observers get better at detecting morphs after looking at a certain number of images. We thus analyze the observer accuracy by dividing the whole set of images into 4 blocks in the D-MAD setting, where each consists of 100 image pairs, and the 2 blocks in the S-MAD setting, where each set consists of 92 images.

1) Results for Experiment-I - D-MAD: As noted in Figure 13, the average accuracy of each observer group increases for every 100 images completed in the case of D-MAD (Figure 13a). Although this is only a preliminary finding, it is clear that by viewing a large number of photographs, observers improve their ability to recognize altered images. A positive interpretation of this observation is that a dedicated training program in examination-based MAD could increase the competence in detecting morphs.

We further validate the observation by conducting a positive trend analysis using the Cox and Stuart Test [41]. We are specifically interested in determining whether there is, in fact, a time-dependent trend by assessing the accuracy of observers for every 100 pairs of photos, which are independent observations. As noted in Table VIII, we see a significant level of the test ($p<0.001$). With obtained $p$-value of the tests for each set of 100 pairs, we conclude with sufficient evidence that seeing a larger amount of D-MAD pairs improves the accuracy.
Fig. 13. Improvement in MAD accuracy over the total number of images seen.

| Increasing Trend | False | True | True |
|------------------|-------|------|------|
| p-value          | 0.642 | <0.001 | <0.001 |

of the observer. This discovery strengthens the argument that observers should receive training where they can see a variety of new cases to hone their detection abilities.

We also add the hypothesis that seeing more examples will improve the detection accuracy of our test. For this aspect, we draw observers randomly from total observer populations and conduct a One-way analysis of variance [42]. We note the average accuracy for each category with 57.54%, 62.95%, 66.44% and 69.47% with \( p < .0001 \) supporting our observation that the accuracy increases with examples seen.

2) Results for Experiment-II - S-MAD: While a similar conclusion cannot be derived from S-MAD settings depicted in Figure 13b, we can only speculate on the difficulty of the issue and come up with better training methods for morph detection based on single photos. We further assert that better competence through training programs on an understanding of image quality help in future works.

I. Bona Fide Versus Morphed Image Detection in ABC Gate Settings in D-MAD

In this part, we examine the function of ABC gate images and morphed images shown alongside as in a border-crossing scenario to detect morphs. As noted in Figure 14, the accuracy of the MAD increases when the ABC gate images are provided as a reference image. We specifically note an increase of 10% in detection accuracy for female subjects while the accuracy improvement for morphed images of male faces results in around 5% average accuracy.

We conduct a Kruskal–Wallis test between two detection groups when the ABC gate images are available versus when not-available to see whether the ABC gates help in detecting morphed images to a greater extent (\( n = 80, 80 \) correspondingly). We note a \( H(1) = 7.55, p = 0.006 \) for male face images and \( H(1) = 2.81, p = 0.093 \) for female face images. We conclude that there is no real advantage for spotting morphed images when ABC gate images are provided. Our hypothesis here is that the face images of female subjects vary significantly due to varying hairstyles and everyday makeup making the observers not detect all the morphed images. However, this requires additional research, which will need enlarging the dataset with and without make-up. While it is noted that the average \( p \)-value for male and female face images is \( H(1) = 6.36, p = 0.011 \) suggests the need for more reliable live capture to improve the detection. We further hypothesize that high-quality live images from ABC gates could generally provide more details for border guards, examiners, etc., making comparisons and making MAD easier.

V. MAD ALGORITHMS V/S OBSERVER ACCURACY

We further analyze the performance of human observers against two algorithms in both categories of D-MAD and S-MAD as explained in the section below.

1) Results for Experiment-I - D-MAD: We select Deep Feature Difference (DFD) [20] and Local Binary Pattern - Support Vector Machine (LBP-SVM) [23] to compare the automated D-MAD algorithms against average human observer accuracy as both the algorithms were evaluated under the NIST FRVT MORPH challenge [7]. While DFD [20] obtained best performance in detecting digital images, LBP-SVM [23] obtained reasonable accuracy in the NIST FRVT MORPH challenge [7]. As noted from the results in Table IX, DFD [20] obtains very high accuracy and LBP-SVM [23] obtains random accuracy of 50%. The human observer accuracy in best case is 64.61%, which is better than the weakest algorithm but less accurate than DFD [20]. The high accuracy of DFD can be attributed to extracting identity-specific features for detecting morphs. To demonstrate incorrect classifications in bona fide and morph attacks, we also include the violin plots for APCER and BPCER in Figure 15.

2) Results for Experiment-II - S-MAD: We compare the typical human observer accuracy to two cutting-edge S-MAD methods. We choose Hybrid features [28] and Ensemble features [43] for detecting morphing attacks based on the performance obtained in the NIST FRVT MORPH challenge [7] with the best performance in detecting printed-and-scanned morph images. The Ensemble features [43] combine textural features with a collection of classifiers, in contrast to the Hybrid features [28], which mix scale space, color space, and numerous classifiers.
present the accuracy in Table X for two chosen algorithms and average human observer accuracy. We note that both algorithms perform better than the human observers in S-MAD for both chosen algorithms, indicating the challenging nature of detecting morphs when no reference image is available. To further demonstrate incorrect classifications in genuine and morph attacks in an S-MAD environment, violin plots for APCER and BPCER are shown in Figure 16.

VI. SUMMARY OF KEY FINDINGS AND THEIR IMPLICATIONS

Based on the analysis presented in previous sections, we note a few major observations in this section and discuss their implications:

- Availability of reference image: Generally speaking, S-MAD settings have a lower detection accuracy than D-MAD settings. It can be deduced that observers
Impact of prior training: When examining the average accuracy, both in S-MAD and D-MAD scenarios, observers with prior training in face comparison tend to do better than observers with prior experience in document examination Figure 8 and Figure 9. An implication of this analysis directly suggests that certain elements of MAD in facial comparison training may be beneficial to include.

Impact of participation: Through analysis, we find that just by taking part in the experiments, observers become better at detecting the morphed images. Specifically, we note the improvement in accuracy throughout the experiment and after seeing several examples (Figure 13). This supports our earlier finding that specialized training programs and teaching observers with varied instances will increase detection accuracy. This observation is also in line with research done on the effectiveness of courses in facial comparisons, where the researchers suggest that

make a better decision when a reference image is available.

| Data          | Approach                  | Accuracy | APCER | BPCER |
|---------------|---------------------------|----------|-------|-------|
| Digital       | Ensemble Features [43]    | 70.00    | 30.00 | 30.00 |
|               | Hybrid Features [28]      | 73.34    | 3.33  | 76.66 |
|               | Average Observer Accuracy | 58.17    | 38.40 | 45.31 |
| Print-Scan    | Ensemble Features [43]    | 63.34    | 36.66 | 36.66 |
|               | Hybrid Features [28]      | 56.67    | 3.33  | 80.00 |
|               | Average Observer Accuracy | 53.88    | 32.23 | 60.02 |
| Post-Processed | Ensemble Features [43]    | 70.00    | 26.66 | 33.33 |
|                | Hybrid Features [28]      | 66.67    | 6.66  | 76.66 |
|                | Average Observer Accuracy | 57.96    | 38.78 | -     |
| Post-Processed | Ensemble Features [43]    | 60.00    | 30.00 | 40.00 |
|                | Hybrid Features [28]      | 56.67    | 3.33  | 76.66 |
|                | Average Observer Accuracy | 54.23    | 31.51 | -     |

*Note: BPCER is not reported in cases where there were not enough samples used for human observer analysis.
examination-based training could be an important part of a training program [44]. To find out if this also applies to MAD, more investigation is necessary.

We thus answer the initial questions posed in this article:

- **How good are ID document examiners at detecting morphing attacks?**
  - The performance of identity document examiners varies depending on their field of employment and they are nonetheless susceptible to errors in the detection of morphing attacks (refer to Figure 10b and Figure 10a).

- **Are people with certain types of training better than others at detecting morphing attacks?**
  - The accuracy of various groups of observers indicate that some methods of training were more effective for MAD than others.

- **Does long experience working in a certain field (for instance, facial examination in ID control) positively impact performance?**
  - We note an indicative correlation between detection accuracy and experience in the line of work. Face comparison experts perform better in identifying morphs, which may indicate a favorable influence of prior experience over observers in other fields of work.

- **Are expert observers with training or experience in checking identity/identity documents better than those without training?**
  - The observers with no training can perform as well as human experts with training. However, it should be noted that the average error rate of those who have received training is significantly lower than that of those who have not (for document training and facial examination) indicating the effect of training.

- **How do MAD algorithms perform compared to human observers?**
  - The algorithms perform better in both S-MAD and D-MAD settings as compared to human observers, indicating a gap in the ability to detect morphs as efficiently as algorithms (refer to Table IX and Table X).

### A. Future Directions

Understanding the improvement in detection accuracy when observers with varying levels of competence select a particular image is one of the prospective avenues for subsequent research. For instance, it would be interesting to understand if border guards and expert facial examiners consider different facial properties before deciding on an image as a border guard in many countries often have some document training. Designing better algorithms and including the factors that people consider when choosing the best course of action could result in a greater understanding of the decision-making process. Furthermore, obtaining the confidence of observers in the decision-making process can be used to fully understand what experts observe in an image to deem it as a morphed image.

A question that needs to be answered in the future is whether ID examiners with training in MAD perform better than people with no MAD training. The impact of training may also be measured, which is interesting. The ability of super recognizers to recognize morphing attacks intuitively without training is a crucial issue that needs to be investigated. In the current study, we have 23 super recognizers, and a dedicated study on super recognizers is currently being conducted whose findings will be reported in the follow-up work.

### B. Potential Errors in the Study

We recognize that the study may, in some cases, be prone to error. For instance, participants may have exerted more effort and spent more time on the tasks in the experiments than they would have in a real-life scenario if they were aware that they were being tested. In contrast, other participants may have spent less time and made less effort, as it was not a real case they were working on.

We also acknowledge that by periodically updating the participants on their results throughout the experiment, we may have introduced bias. It might have had an impact on the findings regarding whether exposure to numerous morphed images improves performance. Given that the experiments would have been an additional task on top of their regular work, fatigue may have also been a factor and negatively impacted performance.
The time the participants spent on the experiments could also be prone to errors, as participants may not have clicked on the “Continue later” button if they, for example, were interrupted during the experiments. Additionally, participants may have experienced stress if they were aware that the time spent was being recorded. More research is needed to fully understand these factors.

VII. CONCLUSION

MAD has been extensively studied using automated algorithms, and a very limited set of works have investigated the detection ability of human observers in detecting morphs. We compare face images in two different settings - S-MAD and D-MAD using human observers in everyday professional life as a benchmark. With the help of 48 different subjects, 400 morphed images were produced using the Differential-MAD (D-MAD) setting, and 400 probe images were taken at the ABC gate to represent a border-crossing scenario. In addition, a new database of 180 morphed images was developed under the Single Image - MAD (S-MAD) setting. The benchmark analyzed with 469 observers for D-MAD and 410 observers for S-MAD from more than 40 countries indicates the challenging nature of morphed image detection. According to the analysis, close to 30% of morphed images were missed by ID experts due to a lack of competence. Numerous subanalyses also show that different observers from various fields of expertise have varying degrees of proficiency in spotting morphing attacks. The analysis also shows early signs of enhanced morphing detection if the observers receive specialized morphing detection training.

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