F. Boutros, N. Damer, M. Fang, M. Gomez-Barrero, K. Raja,
C. Rathgeb, A. Sequeira, and M. Todisco (Eds.): BIOSIG 2024,
Lecture Notes in Informatics (LNI), Gesellschaft für Informatik, Bonn 2024

Development of Novel 3D Face Masks for Assessment of Face Recognition Systems

Lambert Igene[1] †, Afzal Hossain[1], Richard Plesh[1], Sandip Purnapatra[1], Surendra Singh[1], Masudul Imtiaz[1], Stephanie Schuckers[1]

Abstract: Face recognition is integral to identity management and access control systems, but the rise of biometric face recognition has raised concerns about the vulnerability of Presentation Attack Detection (PAD) to various attacks. This paper focuses on developing and evaluating novel, low-cost 3D presentation attack instruments (PAIs) to test the performance of advanced biometric systems. Our PAIs include specialized bobbleheads, white resin 3D-printed masks, white filament 3D masks, masks with image projections, and projections on generic mannequin heads. This project aims to create a diverse, cost-effective PAI dataset to enhance PAD training. We evaluated the effectiveness of these 3D PAIs using three algorithms (Fraunhofer IGD, CLFM, and FaceMe) from the Liveness Detection Face Competition 2021 (LivDet Face, 2021). Additionally, we conducted a comparison between PAIs and bona fide samples using the ArcFace face comparator, achieving an Imposter Attack Presentation Match Rate (IAPAR) of 70% for bobbleheads and 43% for white resin with projection. Our preliminary assessment indicates an Average Classification Error Rate (ACER) of 10.6%, demonstrating the potential of these new PAIs to improve PAD training.

Keywords: Face recognition, Biometric systems, Presentation Attack Detection (PAD), 3D presentation attack instruments (PAIs), Low-cost PAIs, Bobbleheads, 3D-printed masks, Image projection, Diverse dataset, PAD training, LivDet Face 2021, ArcFace comparator, Imposter Attack Presentation Match Rate (IAPAR), Average Classification Error Rate (ACER).

1 Introduction

Biometric recognition, the process of identifying individuals based on unique biological or behavioral traits, has gained extensive use across various sectors and government organizations. Among these biometric traits, facial recognition stands out due to its ease of data acquisition and high accuracy. However, this also makes it susceptible to presentation attacks using Presentation Attack Instruments (PAIs), such as face masks developed from a single target image to deceive Presentation Attack Detection (PAD) systems. Presentation attacks pose a significant threat to the integrity of face recognition systems, as they can effectively mimic real users and bypass security measures.

The primary defense against these attacks is PAD systems, which aim to detect all forms of PAIs. The success of PAD systems heavily relies on the diversity of their training datasets. Exposure to various types of PAIs enhances the algorithm's ability to respond effectively.

[1] Department of Electrical and Computer Engineering, 8 Clarkson Ave, Potsdam USA
†igenela@clarkson.edu, afhossa@clarkson.edu, pleshro@clarkson.edu, purnaps@clarkson.edu, sursing@clarkson.edu, mimtiaz@clarkson.edu, sschucke@clarkson.edu

PAIs can be categorized into three levels: Level A includes paper displays; Level B encompasses display attacks and 2D masks; and Level C involves 3D face masks, which are the most sophisticated and expensive attacks. The high cost of producing 3D masks limits the number available for creating a comprehensive training dataset, making it imperative to develop cheaper alternatives for 3D face PAIs to ensure robust protection of face recognition systems.

This project focuses on producing cost-effective 3D face masks that still contain detailed 3D structural information of the target subject, captured under various lighting conditions. By developing and evaluating novel, low-cost 3D PAIs, we aim to enhance the training and effectiveness of PAD systems, thereby improving the overall security of biometric face recognition technologies.

Prior research has focused on high-quality PAIs with little data variability as some datasets are not made publicly available. Table 1 shows a comparison of datasets used in previous work.

Tab. 1: A comparison of datasets used in previous work

Previous work	Details	Description
Neslihan et al [KD12]	Dataset: Morpho	Availability: Non-public
	Mask type: 2D, Display	Material: A4 printed, video replay
	Sensor: VIS, NIR	Comparison: No
	PAD analysis: Commercial	Feature: Texture and motion discriminant only
Nesli et al [EM14]	Dataset: Morpho, 3DMAD	Availability: Public
	Mask type: 2D, 3D	Material: 3D Paper mask, 3D resin mask
	Sensor: 3D Scanner, Microsoft Kinect Sensor	Comparison: Yes
	PAD analysis: Internal (ML)	Feature: Motion and planar of object discriminant
Ketan et al [KBM19]	Dataset: XCSMAD	Availability: Non-public
	Mask type: 3D-photo, display	Material: Silicon mask
	Sensor: VIS, NIR, Thermal-LQ, Thermal-HQ	Comparison: Yes
	PAD analysis: Internal (CNN)	Feature: CNN to extract a feature-vector (FV)
		Note: Silicon masks are quite expensive
LivDet2021 face [Pu21]	Dataset: Clarkson University (CU) and Idiap Research Institute	Availability: Non-public
	Mask type: 2D, 3D and Display	Material: Paper-displays, laptop-display, 2D photo masks, 3D-masks, silicon-masks, video display
	Sensor: Mobile camera sensors, Basler camera	Comparison: No
	PAD analysis: Academic	Feature: Analysis of submitted PAD systems using a robust dataset
Our work	Dataset: Novel 3D mask	Availability: Public
	Mask type: 2D, 3D, and Display	Material: Bobblehead, HQ 3D-mask, White 3D-mask (Resin/Filament) w/ and w/o projection, Mannequin Head
	Sensor: Mobile Camera Sensors	Comparison: Yes
	PAD analysis: Academic	Feature: Analysis of 3D mask performance on PAD systems, using newly developed cost-effective PAIs

1.1 Literature review

Datasets are crucial for training and testing Presentation Attack Detection (PAD) systems. The Morpho dataset, which has yielded good results, is a level B, 2D set, thus limiting its predictive power for 3D mask testing [KD12, Ch11, Ch16].

The Silicon 3D Mask Dataset (XCSMAD) was used to train a Convolutional Neural Network + Logistic Regression (CNN+LR) PAD system [KBM19]. This algorithm performed exceptionally well, achieving an average Equal Error Rate (EER) of 0.6% on 3D data captured with a high-quality thermal (THE-HQ) sensor, and 0.8% on data captured with visible light (VIS). However, creating silicon 3D masks is costly and requires substantial investment. This has led to the exploration of less expensive approaches for 3D mask creation.

Recent studies have further evaluated the performance of PAD algorithms in 2D and 3D spoof detection [KD13, Ig24]. The Center for Identification Technology Research conducted the LivDet 2021 Face evaluation[Pu21], assessing academic algorithms on a diverse dataset comprising photo paper, laptop displays, 3D masks, and silicon masks of varying quality levels. This dataset, collected using multiple image-capturing sensors, showed a winning Average Classification Error Rate (ACER) of 16.5% and a Bonafide Presentation Classification Error Rate (BPCER) of 15.3% for the image category. For the video category, the winning ACER was 13.81% and the BPCER was 14.3%. These results highlighted the need for continued research and improvement of PAI datasets.

Our primary objective is to curate a diverse dataset featuring innovative and cost-effective 3D face masks of various qualities. This initiative aims to enrich the array of Presentation Attack Instrumentation (PAI) types available for comprehensive training and testing of PAD systems, thereby minimizing susceptibility to presentation attacks.

Addressing the economic challenges associated with developing and printing 3D colored masks, our study introduces cost-effective bobbleheads, white 3D resin masks, and white 3D filament masks. Each mask is crafted to emulate the bona fide subject's facial appearance structurally. Contrary to the common perception of bobblehead models as animated representations, our research reveals that well-designed bobbleheads successfully capture facial features that mirror reality or closely resemble the targeted subjects, potentially deceiving face recognition systems. The face projection technique provides color and texture to the white filament and resin-printed 3D masks, offering a realistic human appearance during data collection. Additionally, we introduce a non-structural resemblance model by projecting facial images of target subjects onto 3D mannequin heads. These 3D PAIs are designed to augment PAD system evaluation while maintaining economic feasibility.

Given that our dataset has not been previously used, we conducted a comparison between bona fide subject images and the newly created PAI samples using the ArcFace face comparator to gain insights into their similarity.

Our contributions also include an evaluation of the impact of our newly developed PAIs on PAD algorithms. The outlined objectives and distinctive contributions of this study are as follows:

- Construction of 3D facial models from sets of 2D images, translated into 3D masks using graphic design tools such as AutoCAD Recap, Meshmixer, and Blender for creating high-quality, multi-image masks. This process applies to white 3D masks and more expensive color 3D masks.

- Creation of cost-effective bobbleheads representing 3D models of faces, providing an economical alternative to traditional 3D color-printed masks.

- Implementation of subject face projections onto white 3D-printed masks and mannequin heads.

- Data collection using DSLR cameras, iPhones, and Samsung S9 camera sensors to ensure maximum diversity within the dataset.

- Assessment of the effectiveness of generated PAIs by evaluating the comparison of target bona fide subjects and PAD performance on PAIs.

These contributions advance the field by providing additional diversity and cost-effectiveness for 3D PAI species compared to prior work.

2 PAI Development and Testing Methodology

The testing dataset was collected using three camera sensors, with data partitioned into live and Presentation Attack Instrument (PAI) samples of level C. The distribution of the data is outlined in Table 2.

Following the guidelines of ISO/IEC 30107-3 [Po13], we assessed the performance of our PAIs using two primary metrics: Attack Presentation Classification Error Rate (APCER) and Bonafide Presentation Classification Error Rate (BPCER) on PAD algorithms. APCER signifies the proportion of attack presentations incorrectly classified as bonafide, while BPCER represents the proportion of bona fide presentations misclassified as attacks. We also computed the Average Classification Error Rate (ACER), the mean of APCER and BPCER. Both APCER and BPCER were assessed at a threshold of 50, as utilized in the LivDet Face 2021 competition [Pu21].

2.1 Bobblehead

For this PAI species, a single image of the target subject was used to develop a bobblehead 3D model. Data was collected from five unique subjects and sent to the manufacturer, bobblehead.com. The manufacturer first hand-sculpted the head of the target subject, then created a mold and cast of the face from the 3D-built sculpture. The final stage involved painting the finished bobblehead. An example of this process can be found in Figure 1.

2.2 White Resin (WR) and Filament 3D Masks (WF)

Using an AutoCAD 3D reconstruction model, at least 40 images from various angles of a live subject's face were collected and uploaded into the model. Reconstruction time varied between 30 minutes to 1 hour. After generating the 3D model, editing, and cropping were performed using Blender or Meshmixer. The skin tone rendering was removed, and the finished model was exported to a USB drive. Two distinct masks were printed, one with resin and the other with filament materials. These materials were chosen for their different reflectance properties: resin has low reflectance power, and filament has high reflectance power. The masks were produced at the Clarkson University Makerspace workshop using a Prusa MK3 3D printer for filament and FormLabs for resin printing.

2.3 Projection of Face Image on White Resin (WRP) and Filament Mask (WFP)

For this PAI species, a single-face image of the target subject was projected onto the white resin and filament 3D-printed masks using a Miroir M600 projector with a resolution of 1920 x 1080 pixels. Images were then captured under different lighting conditions: lights off, lights on with low intensity, and lights on with high intensity.

2.4 Projection of Face onto a 3D Object (MHP)

For this PAI species, a face image was projected using a Miroir M600 projector onto a white mannequin head. This method does not retain the 3D structure of the target face but uses a generic face model with typical human features such as eyes, ears, mouth, and nose. Images were captured under the same lighting conditions as the white resin and filament masks with projection.

2.5 High-Quality (HQ) 3D Mask

The same 3D face reconstruction process used for the white resin and filament 3D masks was employed here, with one difference: after cropping and editing, the facial rendering of the subject was not removed, and thickness was added using the Blender graphic tool. The finished 3D mask model was then sent to i.materialise[i.24], a 3D printing company in Belgium, for 3D color printing. Data was captured from the 3D HQ multiple-image mask using a camera sensor under full and low-light conditions.

Fig. 1: Bobblehead development process from left to right: Bona fide subject, side view of the sculpted model, front view of the sculpted model, finished bobblehead.

Fig. 2: Example images of PAI types developed. From Top left to right: Bobblehead, white Resin 3D mask, white resin with projection, high-quality 3D mask, a white filament with projection, hair feature on white filament with projection, white filament 3D mask, projection of face onto a 3D mannequin head.

2.6 Data collection description:

To set up and capture our data using the newly developed PAIs, standard conditions and equipment including a camera sensor, projector, 3D mask, and mannequin were used, and captured data at a straight-on angle. These did not change over the course of data collection. We varied the lighting conditions, the distance between the model and the projector, and the distance between the model and the camera sensor. Table 2 shows the distribution of the images from the data collection and Figure 3 shows the setup for data collection.

- Distance between the model and the projector: The images were projected using a Miroir projector with a display resolution of 1920 x 1080 pixels, and distance varied between 60cm to 80cm depending on the point at which the projection aligned with the 3D mask model.

- Lighting Conditions: The data collection encompassed various lighting scenarios, including both lights-off and lights-on conditions during projection and lights-on in full intensity and lights-on in low intensity for colored 3D mask data collection to ensure robustness under diverse environmental settings.

- Distance between model and camera sensor: The distance between the model and the camera varied between 60cm to 80cm but the angle remained straight-on for all data collection, ensuring consistency in angle across all experiments.

- Camera Sensors: A comprehensive approach was adopted for image acquisition, utilizing three different camera sensors for versatility and thoroughness. The Canon EOS 70D DSLR, iPhone 14, and Samsung S9 cameras were employed to capture images, allowing for a multi-faceted dataset.

Fig. 3: Setup for projection data collection using a Miroir M600 projector, a mannequin head, and a white 3D-printed mask.

Tab. 2: Test Dataset Summary

Class	Type of PAI	Total	Sensor
Bona fide	-	135	DSLR, iPhone X, Samsung S9
PA	Bobblehead	90	DSLR, iPhone 14, Samsung S9
PA	White filament mask	150	DSLR, iPhone 14, Samsung S9
PA	White resin mask	90	DSLR, iPhone 14, Samsung S9
PA	Resin mask with projection	90	DSLR, iPhone 14, Samsung S9
PA	Filament mask with projection	150	DSLR, iPhone 14, Samsung S9
PA	Mannequin head with projection	150	DSLR, iPhone 14, Samsung S9
PA	HQ 3D Mask	90	DSLR, iPhone 14, Samsung S9

3 Results and Discussion For Comparison

The developed PAIs were tested using an Arcface comparator to determine if the 3D mask matched the target's live face [Mo17, Se16]. This step aimed to determine the effective-

Tab. 3: Imposter Attack Presentation Match Rate (IAPAR) 3D PAI species compared to target bona fide image using ArcFace comparator with cosine similarity at a 0.55 threshold

PAIs	IAPAR (%)
Bobblehead	70.0
White Filament	34.0
White Resin	19.5
White Filament with Projection	38.0
White Resin with Projection	43.0
Mannequin with Projection	31.2
HQ 3D Mask	76.5

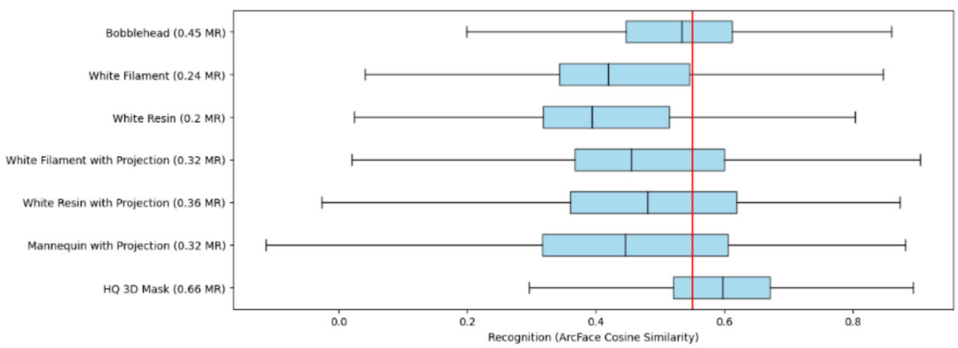

Fig. 4: Boxplot of cosine similarity scores for each PAI species (The higher the cosine distance, the better the match)

ness of the PAI species in a face recognition system. Figure 4 displays the cosine similarity score distribution for each PAI species, based on a baseline threshold set at 0.55, as established in previous analyses [Pu21]. Several experiments were conducted using Arcface [De19], each yielding comparison results detailed in Table 3, showing the Imposter Attack Presentation Match Rate (IAPAR) at a specified threshold value of 0.55. We performed comparisons between mated live and spoof subjects. The new species matched the target individual showing an IAPAR of 70% in bobblehead and 42.89% and 37.94% in white resin with projection and white filament with projection, respectively. Even the white filament, and resin mask without projection achieved an IAPAR of 34.0% and 19.5%, respectively. With the high IAPAR achieved we believe these additional PAI species will add value in the training and testing of PAD algorithms to improve the performance of face recognition systems.

4 Results and Discussion For PAD Testing

In the second phase, we conducted testing for PAD using the PAD algorithms submitted in Livdet Face 2021. The assessment involved three algorithms (Fraunhofer IGD, CLFM, and FaceMe). This data was not provided to the competitors and it is unlikely that the PAD

Tab. 4: APCER and BPCER for each PAI Species

PAD Algorithm Name	Presentation Attack Instruments Level Types (APCER %)							Overall Performance (%)		
	Bobblehead	**WF**	**WR**	**MHP**	**WRP**	**WFP**	**HQ 3D Masks**	**APCER$_{avg}$**	**BPCER**	**ACER**
Fraunhofer IGD	32.2	0	0	0	0	2.0	6.7	5.8	15.3	10.6
CLFM	43.3	0	0	4.0	0	0	27.8	10.7	24.1	17.4
FaceMe	28.9	11.3	10.0	0.7	0	0	16.7	9.7	16.1	12.9

algorithms were trained on data similar to ours. The detailed functionality of these models is extensively discussed in [Pu21].

Table 4 illustrates the performance comparison of the algorithms submitted on unseen PAIs in this new dataset. The test results indicate that Fraunhofer IGD has the lowest average ACER at 10.6%, closely followed by FaceMe at 12.9%, with CLFM, achieving the highest at 17.4% and the highest BPCER at 24.1%. Fraunhofer IGD at 15.3% had the best BPCER for live sample testing and FaceMe at 16.1% closely followed. All three algorithms effectively detected white resin with projection with a 0% APCER. However, we see varying APCER results on various white filament and white resin testing samples. The performance breakdown for other PAIs is detailed in Table 4. For bobblehead PAI, FaceMe achieved the best APCER at 28.9%, followed by Fraunhofer IGD at 32.2%, and CLFM at 43.3%. As a benchmark, for High-Quality 3D Masks, the Fraunhofer IGD Pad algorithm outperformed others with an APCER of 6.7%, followed by FaceMe at 16.7%, and CLFM at 27.8%.

4.1 Challenges with PAD Algorithms in Detecting High-Quality 3D Masks and Bobbleheads

Further analysis from Table 4 indicates that PAD algorithms were not effective in detecting high-quality 3D masks and bobblehead samples. The algorithms exhibited poor performance during testing. This outcome may be attributed to the bobblehead models carrying live features such as hair and skin tone, making it challenging for PAD algorithms to discern. In contrast, PAD algorithms were able to detect face projections on mannequin heads, white filaments, and white resin 3D masks. This may be due to the light intensity of the projector used for projection; brighter illumination may enhance the effect these PAIs have during testing. The success of PAD algorithms in face projection experiments may also be attributed to digital artifacts left in the captured image by the projection process and the absence of human features like hair, which may signal to the PAD algorithms that the sample is a mask, thereby simplifying detection.

Comparing PAD analysis in Table 4 to comparison performance in Table 3, the results indicate that 3D high-quality masks achieved a true accept rate of 76.5%, confirming that PAD algorithms found them difficult to detect. Despite the low comparison rates observed in Table 3 for white resin and white filament 3D models, the FaceMe PAD algorithm was not able to detect all PAI samples, achieving only an APCER of 11.3% and 10%, respectively. This phenomenon is likely due to the ability of these 3D masks to carry live features like hair, eyes, and proper skin tone during projections.

The addition of live features like hair on white resin and filament 3D masks, as shown in Figure 2, makes these presentation attack instruments more challenging for PAD algorithms to detect. Despite these challenges, the fairly accurate detection of white resin and filament masks indicates that not all PAD algorithms may be robust against these attacks.

It is noteworthy that the introduced PAIs were not part of the algorithms' training dataset. This deliberate exclusion aimed to assess how the models would perform on entirely new or unfamiliar PAIs, simulating the challenges faced in a continually evolving environment.

While our experimental results suggest that the face PAD algorithms in this study perform well with PAIs featuring minimal or no texture rendering, other PAD systems may still benefit from this enhanced dataset for the training of biometric PAD systems. Providing more exposure of PAD systems to a diverse PAI dataset is crucial to address the escalating threat of presentation attacks on biometric face recognition systems. This can now be achieved at a reduced cost with the 3D PAIs introduced in this study.

5 Conclusion

The primary objective of this project is to introduce novel Presentation Attack Instrument (PAI) species and develop a cost-effective PAI dataset, facilitating the testing of presentation attack detection algorithms on face biometric systems. The following are the outcomes of this study:

(a) Seven low-cost innovative PAIs, including bobbleheads, white filament 3D masks, white resin 3D masks, white filament 3D masks with image projection, white resin 3D masks with image projection, mannequin heads with image projection, and high-quality 3D masks were developed. Data made available on request at [Un24].

(b) A comparison analysis of all developed PAIs to bona fide subject data was carried out with IAPAR as high as 43%, 70%, and 76.5% for white resin 3D masks with projection, bobblehead, and high-quality 3D masks, respectively.

(c) A comparative analysis of all developed PAIs using three face biometric PAD algorithms (Fraunhofer IGD, CLFM, and FaceMe) was conducted. The best-performing algorithm achieved an Average Classification Error Rate (ACER) of 10.6%, APCER of 5.8 % and a BPCER of 15.3%.

The inclusion of our developed PAIs, which will be made available to researchers, can bridge the performance and production cost gap observed in the PAD algorithm evaluation and PAI development in face recognition research. This, in turn, has the potential to enhance public confidence and bolster the security of biometric systems.

5.1 Acknowledgements:

This material is based upon work supported by the Center for Identification Technology Research and the National Science Foundation under Grant Nos. 1650503 and 2413228.

References

[Ch11] Chakka, Murali Mohan; Anjos, Andre; Marcel, Sebastien; Tronci, Roberto; Muntoni, Daniele; Fadda, Gianluca; Pili, Maurizio; Sirena, Nicola; Murgia, Gabriele; Ristori, Marco et al.: Competition on counter measures to 2-d facial spoofing attacks. In: 2011 international joint conference on biometrics (IJCB). IEEE, S. 1–6, 2011. 3

[Ch16] Chingovska, Ivana; Erdogmus, Nesli; Anjos, André; Marcel, Sébastien: Face recognition systems under spoofing attacks. Face Recognition Across the Imaging Spectrum, S. 165–194, 2016. 3

[De19] Deng, Jiankang; Guo, Jia; Xue, Niannan; Zafeiriou, Stefanos: Arcface: Additive angular margin loss for deep face recognition. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. S. 4690–4699, 2019. 8

[EM14] Erdogmus, Nesli; Marcel, Sebastien: Spoofing face recognition with 3D masks. IEEE transactions on information forensics and security, 9(7):1084–1097, 2014. 2

[i.24] i.materialise: , 3D Printing Service. https://i.materialise.com/en, 2024. Accessed: 2024-08-23. 5

[Ig24] Igene, Lambert; Hossain, Afzal; Chowdhury, Mohammad Zahir Uddin; Rezaie, Humaira; Rollins, Ayden; Dykes, Jesse; Vijaykumar, Rahul; Komaty, Alain; Marcel, Sébastien; Tapia, Juan E. et al.: Face Liveness Detection Competition (LivDet-Face) - 2024. In: 2024 IEEE International Joint Conference on Biometrics (IJCB). IEEE, S. 1–9, 2024. 3

[KBM19] Kotwal, Ketan; Bhattacharjee, Sushil; Marcel, Sébastien: Multispectral deep embeddings as a countermeasure to custom silicone mask presentation attacks. IEEE Transactions on Biometrics, Behavior, and Identity Science, 1(4):238–251, 2019. 2, 3

[KD12] Kose, Neslihan; Dugelay, Jean-Luc: Classification of captured and recaptured images to detect photograph spoofing. In: 2012 International Conference on Informatics, Electronics & Vision (ICIEV). IEEE, S. 1027–1032, 2012. 2, 3

[KD13] Kose, Neslihan; Dugelay, Jean-Luc: Countermeasure for the protection of face recognition systems against mask attacks. In: 2013 10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG). IEEE, S. 1–6, 2013. 3

[Mo17] Moschoglou, Stylianos; Papaioannou, Athanasios; Sagonas, Christos; Deng, Jiankang; Kotsia, Irene; Zafeiriou, Stefanos: Agedb: the first manually collected, in-the-wild age database. In: proceedings of the IEEE conference on computer vision and pattern recognition workshops. S. 51–59, 2017. 7

[Po13] Podio, Fernando L: Advances in biometric standardisation–addressing global requirements for interoperable biometrics. International Journal of Biometrics, 5(1):5–19, 2013. 4

[Pu21] Purnapatra, Sandip; Smalt, Nic; Bahmani, Keivan; Das, Priyanka; Yambay, David; Mohammadi, Amir; George, Anjith; Bourlai, Thirimachos; Marcel, Sébastien; Schuckers, Stephanie et al.: Face liveness detection competition (livdet-face)-2021. In: 2021 IEEE International Joint Conference on Biometrics (IJCB). IEEE, S. 1–10, 2021. 2, 3, 4, 8, 9

[Se16] Sengupta, Soumyadip; Chen, Jun-Cheng; Castillo, Carlos; Patel, Vishal M; Chellappa, Rama; Jacobs, David W: Frontal to profile face verification in the wild. In: 2016 IEEE winter conference on applications of computer vision (WACV). IEEE, S. 1–9, 2016. 7

[Un24] University, Clarkson: , Clarkson Integrative Tissue Engineering Resource Center (CITER). https://citer.clarkson.edu/contacts/, 2024. Accessed: 2024-08-23. 10