On the Generalisation Capabilities of Fingerprint Presentation Attack Detection Methods in the Short Wave Infrared Domain

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Abstract: Nowadays, fingerprint-based biometric recognition systems are becoming increasingly popular. However, in spite of their numerous advantages, biometric capture devices are usually exposed to the public and thus vulnerable to presentation attacks (PAs). Therefore, presentation attack detection (PAD) methods are of utmost importance in order to distinguish between bona fide and attack presentations. Due to the nearly unlimited possibilities to create new presentation attack instruments (PAIs), unknown attacks are a threat to existing PAD algorithms. This fact motivates research on generalisation capabilities in order to find PAD methods that are resilient to new attacks. In this context, we evaluate the generalisability of multiple PAD algorithms on a dataset of 19,711 bona fide and 4,339 PA samples, including 45 different PAI species. The PAD data is captured in the short wave infrared domain and the results discuss the advantages and drawbacks of this PAD technique regarding unknown attacks.

1 Introduction

Next to knowledge-based and token-based authentication methods, biometric recognition systems are established in our daily life. Common examples include high security border control on the one side, and user convenient smartphone unlocking on the other side of the wide range of applications. The unique link between the observed biometric characteristic (i.e., fingerprint) and the data subject's identity are a main advantage of biometric authentication, since passwords and tokens could be shared among individuals. However, biometric systems are usually exposed to the public and thus vulnerable to presentation attacks (PAs). In this case, no bona fide biometric characteristic but an artificial presentation attack instrument (PAI) is presented to the capture device [2]. The goal of the attacker is either to impersonate another data subject or to conceal the own identity due to black-listing. Since successful attacks [3] are known, (unsupervised) biometric recognition systems require an automated presentation attack detection (PAD) module in order to detect attack presentations and only process bona fide presentations [5]. Within the last decade, researchers proposed a lot of different PAD approaches [6,7], that can be classified into two categories: i) software-based methods, where the captured data of commercial sensors is analysed in a deeper way; and ii) hardware-based methods, where additional PAD data from the biometric characteristic are acquired by an additional sensor integrated in the capture device and then processed with dedicated software.

Fingerprint PAIs can be created from a wide variety of different materials [8] and in shapes of full fake fingers, thin overlays, or simple printouts. These distinct combinations result in various PAI species with different properties. A continuous and unsolvable challenge is to collect a 'perfect' dataset including all PAI species. Hence, it is very important to evaluate the PAD performance on unknown attacks in order to see the generalisability.

In this context, we apply a generalisation protocol on ten fingerprint PAD algorithms in order to analyse their vulnerability towards unknown attack groups. The evaluation is carried out on data captured in the short wave infrared domain with over 24,000 samples, including 45 different PAI species. These PAI species are clustered into similarity groups, which are consecutively left out during training of the algorithms and seen only during the testing.

The remaining article is structured as follows: Section 2 summarises related work on generalisation approaches for fingerprint PAD and Section 3 includes the description of the utilised hardware-based capture device. The PAD methods are introduced in Section 4 and Section 5 discusses the results. Finally, Section 6 concludes our findings.

2 Related Work

A detailed overview of hardware-based fingerprint PAD is presented in [19], hence we focus on unknown attacks [20] and generalisation approaches in this work. A summary of these works is given in Table 1. It should be noted that, most of the reviewed approaches use different datasets and present multiple experiments including leave-one-out (LOO) or cross database/sensor protocols. For LOO experiments, usually one PAI species is left out from training and only used for testing to evaluate the classification of unknown attacks. Hence, a comparison of performance metrics is not included due to its lack of fairness.

Starting in 2010, Tan et al. [9] evaluated different environmental conditions and unseen PAIs during testing. In particular, they used the ridge signal, valley noise, and region labelling, and reported much higher error rates for unknown scenarios than for cases where PAIs are available during training. For their experiments, the authors collected a database using three fingerprint capture devices: Cross-Match, Digital Persona, and Identix. The same devices were also used to collect the LivDet 2009 dataset [21], which was then utilised by Marasco and Sansone [10] to test further PAD methods. Static and

| Year | Description | Ref. |
|------|-------------|------|
| 2010 | Ridge signal, valley noise, region labelling, LOO | [9] |
| 2011 | Static + intensity-based features, LOO | [10] |
| 2015 | Binary SVM based on One-class SVM, Open set | [11] |
| 2016 | One-class SVMs + Score fusion CNNs. Unknown PAs, cross sensor/DB | [12] |
| 2016 | One-class GANs | [13] |
| 2019 | Patch-based LSTM + CNN, LOO | [14] |
| 2019 | Fingerprint Spoof Buster, LOO + best subset | [15] |
| 2020 | Feature encoding. Unknown PAs, cross sensor/DB | [16] |
| 2020 | One-class convolutional autoencoder | [17] |
intensity-based features were extracted from the fingerprint samples and classified in a LOO analysis. Through combining multiple PAD methods, the authors reduced the impact of unknown PAIs during training. Based on the LivDet 2011 dataset [22], Rattani et al. [11] evaluated an open-set scenario on unknown attacks. They create a one-class SVM and fine-tuned it on selected PA samples to produce a binary classifier. This SVM is then used for PAD on partly unknown attacks in the test partition, and is subsequently recalibrated on those new materials.

However, the original LivDet evaluation protocol did not consider unknown attacks at the test stage. LivDet 2015 [23] was the first dataset including three additional unknown attack instruments in the test set. The subsequent competitions, LivDet 2017 [24] and LivDet 2019 [25], have only unknown attacks in the test set and are completely trained on different PAI species.

Recently, the generalisation capabilities of PAD algorithms attracted more attention. In this context, Chugh and Jain [16], performed a LOO analysis of their Fingerprint Spoof Buster [26] on a combined dataset from MSU-FFPAD and PBSKD. Furthermore, they defined a generalisation subset, which includes only six out of twelve PAI species, but enables the detection of the unknown materials due to their similarity. The authors extended this work in [17] and added the LivDet 2017 dataset as well as a proposed universal material generator to create additional synthetic samples for training.

Furthermore, Nogueira et al. [13] report increasing error rates for their CNNs on the LivDet 2011 [22], LivDet 2013 [27], and LivDet 2015 [23] datasets when introducing unknown scenarios. Their experiments include unknown attacks, cross database, and cross sensor protocols. Another generalisation approach was presented by Gonzalez-Soler et al. [13] based on the same three LivDet datasets. The authors propose a combination of local features (scale-invariant feature transform) and three feature encodings: bag of words, Fisher vector, and vector locally aggregated descriptors. Those methods are evaluated on unknown attacks as well as cross-database and cross-sensor scenarios. The results show that the Fisher vector encoding performs best on the different settings.

Following the idea of LOO analysis, Mirzaalian et al. [15] worked on temporal sequences of laser illuminated images from a private dataset. As classifiers they utilise convolutional neural networks (CNNs) and a long short-term memory (LSTM) network. The latter one can directly process temporal information within sequences while classical CNNs are applied on static images. Their results show a slightly better performance for the LSTM. Further PAD approaches consider all PAI species as unknown attacks and train one-class classifiers only on bona fide samples. The test sample is then processed in the same way and the classifier validates whether the current sample is similar enough to the ones seen during training. The idea is that PA samples differ from bona fide ones and thus can be detected. Using one-class support vector machines (SVMs), Ding and Ross [12] trained on twelve different feature sets of the LivDet 2011 database [22]. A subsequent score fusion counters the weaknesses of single SVMs and provides more generalisability. Engelsma and Jain [14] used three different generative adversarial networks (GANs) on an own collected dataset. Their one-class approach is based on the DCGAN architecture proposed by Radford et al. [28]. Finally, Kolberg et al. [19] built a convolutional autoencoder which was trained on bona fide samples captured in the short wave infrared (SWIR) domain between 1200 nm and 1550 nm. Their approach achieved superior detection performance compared to other one-class classifiers such as SVMs or Gaussian mixture models.

3 Capture Device and PAD data

For the data collection, a camera-based fingerprint capture device [23] was used as depicted in Fig. 1. One camera (Basler acA1300-64gm) takes finger photos in the visible spectrum to extract the fingerprint for legacy compatibility. Additional finger vein images can be captured when activating the near-infrared (NIR) LEDs above the finger. A second camera (100 fps Xenics Bobcat 320) captures PAD data in wavelengths between 900 nm and 1700 nm. Both cameras are placed in a closed box next to multiple illumination sources with only one finger slot at the top. Once a finger is placed on this slot, all ambient light is blocked and only the desired wavelengths illuminate the finger. The invisible SWIR wavelengths of 1200 nm, 1300 nm, 1450 nm, and 1550 nm are especially suited for PAD because all skin types in the Fitzpatrick scale [30] reflect in the same way as shown by Steiner et al. [31] for face PAD, but on the contrary PAI species reflect quite different from skin. Hence, SWIR images are captured in each of these wavelengths. Additionally, a 1310 nm laser diode illuminates the finger area and a sequence of 100 frames is collected within one second. Stemming from biomedical applications, this laser sequence is used to image and monitor microvascular blood flow [32]. Since the laser scatters differently when penetrating human skin in contrast to artificial PAIs, this technique qualifies for PAD as well as shown in [33][34].

Example frames of a bona fide presentation acquired at the aforementioned wavelengths are shown in Fig. 2. For the laser sequence data, only one frame is depicted since the subtle temporal changes are not visible in steady pictures. Nevertheless, we can recognise a circle where the finger focuses the finger. On the other hand, the LEDs achieve a much more consistent illumination for the SWIR images, where the skin reflections get darker for increasing wavelengths. The region of interest for all samples comprises 100 × 300 pixels due to the fixed size of the finger slot.
4 Presentation Attack Detection

Based on previously published benchmarks [19, 35, 56], we select the best-performing algorithms in order to evaluate their generalisation capabilities towards unknown attacks. For this purpose, three different classes of PAD algorithms are utilised, which are summarised in Fig. 3 and introduced in the following subsections. Each algorithm produces its own prediction score, thereby allowing a subsequent score-fusion.

4.1 Selected Laser algorithms

Given the laser sequence data, which comprises 100 frames captured at 1310 nm [40], evaluated PAD algorithms based on temporal and/or spatial features. The LSTM [37] is designed to learn long-term temporal dependencies by maintaining a state of the previously seen data. However, it is not designed to process multi-dimensional input and hence is placed on top of a CNN. The CNN structure serves as a feature extraction in order to reduce the dimension of the input data for the LSTM. In case of utilising a pre-trained CNN base, the PAD performance was not sufficient. However, the long-term recurrent convolutional network (LRCN) [48] approach achieved the best results. This recurrent sequence model is directly connected to a visual CNN and jointly trained from scratch to learn temporal dynamics and perceptual representations together (Fig. 3 top). Apart from the LRCN, which is based on VGG16 [39], three additional CNN methods achieved good results. These CNNs receive a 3-dimensional input created from three specific laser frames since literally no spatial changes are visible within the one second sequence. Thus, using all 100 frames in the CNN would more likely result in over-fitting instead of enhancing the detection accuracy. From the pre-trained VGG16 [39] and the VGGFace [40] networks only the last block as well as the prediction layer are re-trained on the PAD data (Fig. 3 mid). While VGG16 was trained on ImageNet [41], VGGFace has seen much more skin during training and we capture four different SWIR wavelengths, [35] defines a multi-spectral pre-processing block that is added in front of the desired CNN. This block 0 (Fig. 3 mid) receives a 4-dimensional image combined from the four SWIR wavelengths and outputs a 3-dimensional image. It is trained together with the last block and the prediction layer in order to automatically find the best-suited transformation. The resulting 3-dimensional output is then fed to the traditional CNNs. From these SWIR PAD algorithms, the three VGG-based networks (VGGFace [40], VGG16 and VGG19 [39]) achieved the best results as well as the MobileNetV2 [56]. The latter one also makes use of residual connections and additional inverted bottlenecks, where previous bottlenecks are residually connected to subsequent ones. Moreover, given the depth of MobileNetV2, only twelve out of 16 blocks are used in order to adjust for the relative small training set in contrast to other deep learning tasks. In general, all four SWIR CNNs apply transfer learning based on a pre-trained network.

4.2 Selected SWIR algorithms

Since classical CNNs require a 3-dimensional (RGB) image as input and we capture four different SWIR wavelengths, [35] achieved the best results as well as the MobileNetV2 [56]. The latter one also makes use of residual connections and additional inverted bottlenecks, where previous bottlenecks are residually connected to subsequent ones. Moreover, given the depth of MobileNetV2, only twelve out of 16 blocks are used in order to adjust for the relative small training set in contrast to other deep learning tasks. In general, all four SWIR CNNs apply transfer learning based on a pre-trained network.

4.3 One-class Autoencoder

All previously named PAD methods are two-class algorithms. However, especially for unknown attack evaluations it is interesting to additionally include one-class classifiers in the experiments. Hence, a convolutional autoencoder [19] (Fig. 3 bottom) is analysed as well. It works on 3-dimensional laser images and 4-dimensional SWIR images likewise. The encoding phase repeatedly reduces the input dimension until it results in a 1-dimensional latent representation of fixed size. Subsequently, the decoding phase reconstructs the original image size. The final prediction is done by computing the difference between the input and output images. Since the autoencoder is only trained on bona fide samples, it is expected that the reconstruction of PA samples significantly differs from its input and thus can be detected. Previous tests [19] have shown that a fusion of laser and SWIR autoencoders does not improve the PAD accuracy since the SWIR autoencoder on its own performs better. However, we include both algorithms in this new benchmark for completeness.

4.4 Fusion

In contrast to the autoencoder results [19], other approaches [29, 43, 47, 48] have shown improvements for a fusion of laser and SWIR algorithms. However, since the main part of this work consists of analysing the generalisation capabilities, we compute a fixed fusion and evaluate its performance next to the single algorithms on
unknown attacks. In this regard, we combine one laser algorithm with one SWIR algorithm in order to observe to what extent this unknown attacks. In this regard, we combine one laser algorithm with one SWIR algorithm in order to observe to what extent this

5 Experimental Evaluation

5.1 Experimental Setup

The data was collected in four acquisition sessions in two distinct locations within a timeframe of nine months. Subjects could participate multiple times and presented six to eight fingers per capture round including thumb, index, middle, and ring fingers. Fingers were presented as they were, thereby resulting in different levels of moisture, dirt, or ink. The combined database contains a total of 24,050 samples comprising 19,711 bona fides and 4,339 PAs stemming from 45 different PAI species. These PAI species were selected by the project sponsor and include full fake fingers and more challenging overlays as summarised in Table 2. The printouts were also worn as camera-based systems, other groups (e.g. describing the moisture level) would be more relevant than the colour or transparency level. Note that the project sponsor indicated to make the complete dataset available in the near future for reproducibility and benchmarking.

In order to evaluate the generalisation capabilities of the selected PAD algorithms, a leave-one-out protocol is adopted. In particular, the protocol leaves a complete PAI group out of training, which is only used during testing. With 45 PAI species, leaving out a single PAI species at a time would result in a lot of experiments with limited statistical meaning. Hence, we are leaving out complete PAI groups for more relevant results. In addition to the four presented groups in Table 2, another group comprises all overlay PAIs, thus training only on fake fingers.

As a baseline, we utilise the partitioning from [19], where each PAI species is present in training, validation, and test sets. Furthermore, some bona fide samples have been removed in order to grant unbiased training and validation sets with an equal number of PA and bona fide samples, while no data subject is seen during training and testing procedures. For the LOO partitions, one group of 45 PAs is only present in the test set. The remaining PA samples are randomly assigned to the training (85%) and validation (15%) sets. In order to be able to analyse the influence of different PAI groups during the training procedure, the bona fide samples in each set are identical across all LOO partitions; 50% for training, 15% for validation, and 35% for testing. The specific number of samples in each partition is given in Table 3.

The PAD performance is shown in detection error tradeoff (DET) plots and evaluated according to the standard ISO/IEC 30107-3 on biometric presentation attack detection - Part 3: Testing and Reporting [19]. To that end, two metrics are used: Attack Presentation Classification Error Rate (APCER): proportion of attack presentations incorrectly classified as bona fide presentations. Bona fide Presentation Classification Error Rate (BPCER): proportion of bona fide presentations incorrectly classified as attack presentations. It should be noted that the PAD threshold can be adjusted depending on the use case. In general, a low BPCER represents a very convenient system, while a low APCER is more important for high security applications. Since we analyse the generalisability on LOO partitions, we compare the algorithms at the single operation point APCER0.2. This represents the APCER for a fixed BPCER of 0.2%.

5.3 Experimental Results

The first DET plot in Fig. 4 shows the algorithms’ performance on the baseline partition [36]. The best results in terms of low APCER0.2 values are achieved by the SWIR CNNs VGG16 and MobileNetV2, followed by laser CNN VGGFace and laser LRCN VGG16. Hence, we analysed whether these algorithms complement each other and counted the number of identical attack presentation classification errors (APCEs) in common, since it takes advantage of the strengths of different algorithms. This combination of laser CNN VGGFace and SWIR CNN MobileNetV2 has the least identical APCEs, the most generalisable fusion is achieved by using the following weights of Eq. (4):

\[
0.16 \times S_{\text{laser CNN VGGFace}} + 0.84 \times S_{\text{SWIR CNN MobileNetV2}}
\]

In general it makes sense to fuse algorithms which do not have much APCEs in common, since it takes advantage of the strengths of different algorithms. This combination of laser and SWIR approaches improves the PAD performance to an APCER0.2 of 2.74% on the baseline partition. Furthermore, the number of APCEs per PAI group for the four best algorithms and the fusion are given in Table 4. Finally, this fusion of the two algorithms and their weights is now fixed for further LOO experiments to observe the generalisability of single algorithms compared to a pre-defined fusion.

| Table 2 | Summary of PAs in the database with their corresponding group. The number of total samples and the number of variations is given. Variations include e.g. different colours and conductive augmentations. |
|---------|----------------|
| PAI Group | # variations | # samples |
| 3D printed | 2 | 72 |
| dental material | 1 | 33 |
| dragon skin | 3 | 477 |
| ecosflex | 4 | 291 |
| latex | 2 | 147 |
| playdoh | 4 | 116 |
| silly putty | 3 | 55 |
| wax | 1 | 74 |

| Overlay opaque |  |
|----------------|----------------|
| bandage plaster | 1 | 14 |
| dental material | 1 | 51 |
| dragon skin | 1 | 17 |
| ecosflex | 2 | 1035 |
| gelatin | 1 | 194 |
| printout paper | 1 | 49 |
| silicone | 4 | 752 |
| urethane | 1 | 72 |

| Overlay transparent |  |
|----------------------|----------------|
| dragon skin | 1 | 106 |
| gelatin | 1 | 107 |
| glue | 2 | 27 |
| printout foil | 1 | 64 |
| silicone | 1 | 157 |
| wax | 1 | 18 |

| Overlay semi |  |
|---------------|----------------|
| dragon skin | 1 | 47 |
| ecosflex | 1 | 24 |
| glue | 2 | 146 |
| silicone | 1 | 160 |

| Table 3 | Number of samples within the different partitions. |
|---------|----------------|
| Training | Validation | Test |
| Baseline (BF) | 807 | 542 | 16,381 |
| Baseline (PA) | 807 | 542 | 2990 |
| LOO (BF) | 9956 | 3069 | 6686 |
| Fakefinger | 2624 | 450 | 1265 |
| Overlay | 1027 | 238 | 3074 |
| Opaque | 1801 | 354 | 2184 |
| Transparent | 3152 | 674 | 513 |
| Semi | 3299 | 663 | 377 |

[1] https://www.isi.edu/projects/bat1/data
For the following LOO experiments, we present the DET plots for all evaluated algorithms and additionally analyse the two best laser and two best SWIR methods as well as the fusion in more detail. To that end, we also list the corresponding APCES. Starting with the fakefinger group, Fig. 5 shows the results for training on overlay attacks only. The best algorithms have slightly higher APCER\(_{0.2}\) values than on the baseline partition (e.g. SWIR CNN VGG16: 4.35% (+1%)) and our fusion achieves with 5.85% only the fifth place (+3%). On the other hand, SWIR CNN VGG19 improves by 2% to 4.35%. The number of APCES for the best algorithms are presented in Table 5. While the SWIR algorithms only struggle to detect orange playdoh fingers, the laser algorithms additionally have problems with dragonskin fingers. Furthermore, we have three curves for the LRCN and both autoencoders that show considerable worse performance. While the LRCN should usually be able to detect that there is no blood movement, it suffers from the same type of attacks as the autoencoders and other laser CNNs: dragon skin as well as yellow and orange playdoh fingers are hardly classified as attack presentations. On the other hand, different playdoh colours are always correctly classified.

The DET plot for training only on fakefingers and leaving all overlays for testing is shown in Fig. 6. In this scenario, the autoencoders (especially SWIR) perform much better (3rd place) and the fusion achieves the best results, followed by the SWIR CNN MobileNetV2. However, the laser CNN VGGFace (part of the fusion) has the worst detection performance, hence fusing different algorithms would probably further improve the results. Detailed information on misclassified PAs are given in Table 7. The biggest challenge to all algorithms are transparent silicone PAIs when not seen in training. Far better results are obtained for the opaque group (Fig. 7) since the training includes even more transparent overlay PAIs. The fusion as well as the SWIR CNN MobileNetV2 are able to correctly classify all PA samples for a BPCER of 0.2%. The worst algorithm reports an APCER\(_{0.2}\) of 5.63% while all others are at an APCER\(_{0.2}\) around or below 2%. Thus, we can conclude so far that opaque overlay attacks are no threat to the utilised capture device. Particular numbers of APCES for this group are presented in Table 8 showing a slight
Table 7 Number of APCEs at an APCER0.2 on the Overlay partition.

| PAI       | Laser AE | Laser LRCN | Laser SWIR MobileNetV2 | Fusion |
|-----------|----------|------------|------------------------|--------|
| opaque    | 2 5 1 2 0 | 16 4 0 0 0 | 95 20 0 0 0 | 10 70 0 2 1 |
| transparent | 58 39 21 10 6 | 44 33 13 47 25 | 22 18 10 3 2 | 20 8 0 0 0 |
| silicone  | 152 113 97 74 57 | 2 0 0 0 0 | 3 3 0 0 0 | total 15 25 1 0 0 |

Table 8 Number of APCEs at an APCER0.2 on the Opaque partition.

| PAI       | Laser ResNet | Laser VGGFace | Laser SWIR MobileNetV2 | Fusion |
|-----------|--------------|---------------|------------------------|--------|
| bandage   | 0 0 1 0 0    | 7 21 0 0 0    | 5 1 0 0 0    | 3 3 0 0 0 |
| ecoflex   | 42 15 0 5 3  | 21 5 2 0 2    | 60 2 6 0 0    | 4 1 0 0 0 |
| total     | 549 333 150 145 94 | 98 74 55 46 55 | expected, the LRCN still detects blood movement behind the overlays as in [35], which leads to higher classification errors. Table 9 lists detailed numbers of APCEs proving that transparent silicone PAIs are accountable for the major part of misclassified samples. Further occurring errors are not as significant since the fusion detects most of them. In this context, we see a big improvement of the fusion in detecting gelatin and dragonskin PAIs in comparison to the overlay partition results in Tab. 7.

Aligning with the previous experiments, the semi transparent results settle between the opaque and transparent ones as depicted in Fig. 9. As the PAD performance is closer to the opaque one,
In this work, we benchmarked the generalisation capabilities of fingerprint PAD methods on a database captured in the short wave infrared domain that includes more than 24,000 samples comprising 45 PAI species. To that end, we grouped the PAI species in five clusters that are relevant for this capture device: fakefinger, all overlays, opaque overlays, transparent overlays, and semi transparent overlays. For each experiment we left one group exclusively for testing and trained only on all other groups. Thus, we were able to compare the PAD performance on unknown attack species across ten single PAD approaches and one combined fusion. As a result, we observed that opaque overlay attacks are no challenge to this PAD approach (APCER$_{0.2}$ = 0% in the best case) but the risk increases for transparent overlays (APCER$_{0.2}$ ≈ 9% in the best case). In the fakefinger group, mostly orange playdoh fingers trouble the classifier since their appearance resembles very much the bona fide samples in the SWIR domain. As soon as these PAIs are not included in the training set, the classifier does not learn the subtle differences. Finally, the pre-defined fusion of one laser and one SWIR algorithm generalises quite well even if one fusion partner performs much worse than on the baseline partition. This fusion achieves the best performance across all experiments but two; in both times (fakefinger and transparent group) the fusion reports about a 1.5% higher APCER$_{0.2}$ than the best algorithm. However, these results are still among the best (5th for fakefinger and 2nd for transparent group).

### 6 Conclusions

The fusion is among the best-performing algorithms while most APCER$_{0.2}$ values are below 2.2%. APCEs stem from dragonskin, ecolflex, glue, or silicone PAIs as depicted in Table 10. Moreover, also the semi transparent results improve towards the overlay results of Tab. 7.

All in all we have seen that there are no big differences whether the PAD algorithms are trained on all PAI species or only on fakefingers or overlays, respectively. However, detecting unknown opaque overlays is much easier than unknown transparent ones. Hence, the similar performance to the baseline system are due to the specific shares of samples from the different PAI groups. Additionally, for all LOO experiments, the pre-fixed fusion is among the best algorithms. Thus, while single algorithms report a more unsteady PAD performance, the fusion generalises much better across unknown scenarios. Another lessons learned is that the LRCN fails to detect fakefinger PAIs without blood movement when it is trained only on overlay PAIs. Hence, the performance of the LRCN highly depends on the training set and does not really generalise.
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References

1. A. K. Jain, “Technology: Biometric recognition,” Nature, vol. 449, no. 7158, p. 38, 2007.
2. ISO/IEC JTC1 SC37 Biometrics, ISO/IEC 30107-1. Information Technology - Biometric presentation attack detection - Part 1: Framework, 2016.
3. B. Biggio, Z. Akhtar, G. Fumera, G. L. Marcialis, and F. Roli, “Security evaluation of biometric authentication systems under real spoofing attacks,” IET Biometrics, vol. 1, no. 1, pp. 11–24, 2012.
4. A. Hussein, J. Liu-Jimenez, I. Gococochea-Telleria, and R. Sanchez-Reillo, “A survey in presentation attack and presentation attack detection,” in Proc. Intl. Carnahan Conference on Security Technology (ICCAST). IEEE, 2019, pp. 1–13.
5. S. Marcel, M. S. Nixon, J. Fierrez, and N. Evans, Handbook of Biometric Anti-Spoofing: Presentation Attack Detection. Springer, 2019.
6. C. Sosseki and C. Busch, “Presentation attack detection methods for fingerprint recognition systems: A survey,” IET Biometrics, vol. 3, no. 1, pp. 1–15, 2014.
7. E. Marasco and A. Ross, “A survey on anti spoofing schemes for fingerprint recognition systems,” ACM Computing Surveys (CSUR), vol. 47, no. 2, pp. 1–36, 2014.
8. O. Kanich, M. Drahansky, and M. Méz, “Use of creative materials for fingerprint spoofs,” in Proc. Intl. Workshop on Biometrics and Forensics (IWBFW), 2018.
9. B. Tan, A. Lewicke, D. Yamby, and S. Schuckers, “The effect of environmental conditions and novel spoofing methods on fingerprint anti-spoofing algorithms,” in Proc. Intl. Workshop on Information Forensics and Security (WIFS). IEEE, 2010, pp. 1–6.
10. E. Marasco and C. Sansone, “On the robustness of fingerprint liveness detection algorithms against new materials used for spoofing,” in BIOSIGNALS, vol. 8, 2011, pp. 553–555.
11. A. Rattani, W. J. Scheirer, and A. Ross, “Open set fingerprint spoof detection across novel fabrication materials,” IEEE Trans. on Information Forensics and Security (TIFS), vol. 10, no. 11, pp. 2447–2460, 2015.
12. Y. Ding and A. Ross, “An ensemble of one-class SVMs for fingerprint spoof detection across different fabrication materials,” in Proc. Intl. Workshop on Information Forensics and Security (WIFS). IEEE, 2016, pp. 1–6.
13. R. F. Nogueira, R. de Alencar Lotufo, and R. C. Machado, “Fingerprint liveness detection using convolutional neural networks,” IEEE Trans. on Information Forensics and Security (TIFS), vol. 11, no. 6, pp. 1206–1213, 2016.
14. J. J. Engelsma and A. K. Jain, “Generalized fingerprint spoof detector: Learning a one-class classifier,” in Proc. Intl. Conf. on Information Forensics and Security (ICB). IEEE, 2019, pp. 1–8.
15. H. Mirzaalian, M. Hussein, and W. Abd-Almageed, “On the effectiveness of laser speckle contrast imaging and deep neural networks for detecting known and unknown fingerprint presentation attacks,” in Proc. Intl. Conf. on Information Forensics and Security (ICB), 2019, pp. 1–8.
16. T. Chugh and A. K. Jain, “Fingerprint presentation attack detection: Generalization and efficiency,” in Intl. Conf. on Biometrics (ICB). IEEE, 2019, pp. 1–8.
17. T. Chugh and A. Jain, “Fingerprint spoof generalization,” IEEE Trans. on Information Forensics and Security (TIFS), 2020.
18. L. J. González-Soler, M. Gomez-Barrero, L. Chang, A. Perez-Suarez, J. Hernandez-Palancar, and C. Busch, “Fingerprint presentation attack detection based on local features encoding for unknown attacks,” arXiv preprint https://arxiv.org/abs/1908.10163, 2019.
19. J. Kolberg, M. Grimmer, M. Gomez-Barrero, and C. Busch, “Anomaly detection with convolutional autoencoders for fingerprint presentation attack detection,” Arxiv preprint, 2020.
20. J. M. Singh, A. Madhun, G. Li, and R. Ramachandra, “A survey on unknown presentation attack detection for fingerprint,” arXiv preprint arXiv:2005.08337, 2020.
21. G. M. Marcialis, A. Lewicke, B. Tan, P. Coli, D. Grimberg et al., “First international fingerprint liveness detection competition - LivDet 2009,” in Proc. Intl. Conf. on Image Analysis and Processing (ICIAP), 2009, pp. 12–23.
22. D. Yamby, L. Ghi, P. Denti, G. L. Marcialis, F. Roli, and S. Schuckers, “LivDet 2011 fingerprint liveness detection competition 2011,” in Proc. Intl. Conf. on Biometrics (ICB). IEEE, 2012, pp. 208–215.
23. V. Mura, L. Ghi, G. L. Marcialis, F. Roli, D. Yamby, and S. Schuckers, “LivDet 2015 fingerprint liveness detection competition 2015,” in Proc. Intl. Conf. on Biometrics Theory, Applications and Systems (BTAS). IEEE, 2015, pp. 1–6.
24. V. Mura, G. Orri, R. Casula, A. Sibirra, G. Los et al., “LivDet 2017 fingerprint liveness detection competition 2017,” in Proc. Intl. Conf. on Biometrics (ICB), 2018.