Effects of Compression on Attention-based Iris Presentation Attack Detection

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***Abstract*—Biometric recognition systems can automatically recognize individuals using their physical or behavioral characteristics, and they are thus adopted in many applications requiring strong authentication mechanisms. The iris plays a pivotal role among the traits employed for biometric purposes, mainly thanks to the high recognition performance achievable with this modality. While techniques further improving current recognition capabilities are being developed, ensuring the security of these systems against attacks is becoming an increasingly pressing need. This paper deals with presentation attack detection (PAD) for iris recognition, analyzing the effects of image compression on the effectiveness of data-driven approaches. The conducted tests rely on attention-based frameworks, namely vision transformers, to perform PAD while providing suitable tools to argue on the decisions' explainability. The obtained results demonstrate the effectiveness of the employed transformer-based PAD, and the influence of compression on the achievable error rates.**

***Index Terms*—Biometrics, iris, presentation attack detection, compression, attention, explainability.**

I. Introduction

Biometrics represents a reliable and efficient means for automatic people recognition. Creating personal identifiers by exploiting information about what we are, i.e., our physical or behavioral traits like a fingerprint, face, or voice, biometric systems provide greater security and convenience than traditional solutions based on what we know, such as passwords and PINs, or what we own, like tokens [1] [2].

Although numerous advantages are encouraging their adoption, biometric systems are still vulnerable to several potential threats. More in detail, any module characterizing a biometric system, namely the acquisition sensor, the feature extractor, the database, the matcher, and the decision maker, as well as the channels interconnecting them, could be the target of different attacks aiming to corrupt the system integrity [3]. Among the threats mentioned above, sensor attacks, also known as presentation or spoofing attacks, consist of presenting fake biometric traits as system inputs. Since they can be performed without knowing about the inner system mechanisms, they have a particular relevance given that the target biometric data could be acquired in real-life scenarios and then replicated into realistic fake samples. Fine details of faces, fingerprints, and also irises can be in fact easily collected from unaware subjects in a non-authorized way by leveraging on high-resolution cameras [4]. To thwart such risk, presentation attack detection (PAD) mechanisms, also indicated as liveness detection strategies, must be implemented to distinguish genuine biometric samples from spoofed replicas. These solutions are nowadays as important as algorithms improving current recognition performance, and this work is dedicated to analyzing the effectiveness and robustness of PAD methods.

Specifically, the trait considered here is the iris, universally recognized as the modality that ensures the best recognition capabilities in practical biometric systems. While traditionally employed at border crossings or high-security access control checkpoints, recent technological advances have made this characteristic usable in several commercial applications: iris recognition can be implemented in smartphones as an alternative to face and fingerprint, integrated in virtual reality headsets to guarantee connections of the actual user with the digital twin [5], [6] and also employed as a digital key in cryptocurrency identity management systems.

Our analysis of iris PAD is twofold: We first investigate the effectiveness of attention-based classifiers at discriminating between genuine and fake iris samples by exploiting vision transformers (ViTs) for the first time. We also evaluate the influence of a commonly employed image processing step, i.e., compression, on the performance achievable through the considered approaches.

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II. Iris Presentation Attack Detection

As iris recognition became increasingly relevant, thanks to its high accuracy, stability, and resistance to environmental influences, it became a much more worthy target for attacks, including those at the sensor. Presentation attacks against iris recognition systems can take multiple forms [7], including the use of printed iris images [8], textured contact lenses [9], high-resolution digital displays [10], prosthetic eyes [11], and also early-stage post-mortem samples [12]. Among such possibilities, attacks relying on textured contact lenses are considered the most relevant ones, since they can be performed with limited resources and allow attackers to interact naturally with the acquisition sensors [9].

Iris PAD has been traditionally handled by designing handcrafted features to distinguish bonafide samples from impostor attacks [13]. At the same time, the most up-to-date approaches rely on deep learning strategies [14] to achieve better performance, as shown in recent competitions [15]. Despite the significant recent progress [16], some issues and challenges remain. For instance, the influence of several factors on iris PAD has been evaluated, considering the role of image segmentation [17], demographic aspects of the involved subjects [18], and their gender too [19]. The present work aligns in this direction, investigating how image compression can alter the performance of data-driven iris PAD approaches.

A. *Proposed approach for Iris PAD*

While undoubtedly effective in handling several tasks, data-driven models still have downsides affecting their reliability, the most important of which lies in their black-box nature, which often makes their behavior opaque and their decisions hard to interpret. Thus, there has recently been a growing demand for solutions that may guarantee a certain level of explainability in the carried-out tasks to foster users' confidence in these methods' fairness and unbiasedness [20].

In this direction, attention mechanisms are rapidly gaining interest as tools that may provide insights on the aspects driving the performed decisions. Besides that, they can often significantly improve the performance of models that don't use them [21] and are thus applied to an increasing number of applications. Iris PAD is no exception to this trend, with networks equipped with attention mechanisms adopted in [22] where an attention-guided convolutional neural network (CNN) is used to provide visual explanations of model predictions, in [23] where an attention-based pixel-wise method is used to capture fine-grained cues, and in [24] where the last block produced by a CNN is passed to an attention module before taking decisions. In all these cases, attention mechanisms are used with CNN architectures. In contrast, we here evaluate the effectiveness of relying directly and solely on attention mechanisms, as for the *transformer* paradigm [25].

More in detail, we resort to ViT architectures [26] for iris PAD. Such an approach dissects images into fixed-size and non-overlapping patches, with size 16×16 in the considered design, subsequently flattened and linearly embedded into vectorial representations through learnable embedding matrices. A multi-head architecture is then commonly implemented using a series of layers, each consisting of a self-attention contribution [25] followed by a feed-forward network, for each considered head (12 in our case). Using self-attention mechanisms often allows one to outperform traditional CNNs in various vision tasks, especially when dealing with large-scale data [27].

Regarding explainability, processing a new sample with a trained ViT implies computing a series of attention maps at each layer, indicating which areas of the original image are primarily relevant for the desired task. The last layer of each head typically contains higher-level features that directly influence the final decision. The maps computed by different heads can be combined into one by averaging all contributions, thus providing an output robust to the model fluctuations that can be used to demystify the ViT behavior.

III. Image Compression

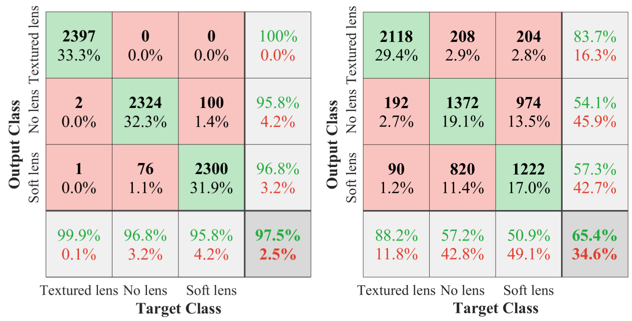
Image compression is a common processing step adopted in basically every application to reduce system requirements in terms of storage space and transmission bandwidth. While lossless compression may be effective in some scenarios, the lossy approach is the most used since notable advantages may often be achieved with limited perceivable quality reduction. Due to its ubiquitous usage, the effects of compression on the recognition performance of biometric systems have been investigated in several papers [28], focusing mainly on widespread traits such as fingerprint [29], face [30], or iris [31]. Such studies are motivated by the fact that, in practical systems, it is crucial to analyze which compression levels could be employed when storing/transmitting biometric samples without significantly affecting the achievable recognition performance.

Regarding iris biometrics, the impact of compression on recognition performance has been investigated in several papers [32]–[34] for lossy and lossless codecs, by comparing templates generated from original and decompressed images. Recently, also deep-learning-based compression schemes have been considered, with performance evaluated in terms of rate-distortion and recognition accuracy [35].

In this paper, we investigate the effects of JPEG and JPEG2000 compression on iris PAD for the first time. As it will be detailed in the following sections, we relate rate-distortion performance measured in terms of the percent root square difference (PRD) to the recognition accuracy of the considered iris-based recognition systems.

IV. Experimental Tests

Experimental tests were conducted on the "Notre Dame Contact Lenses Dataset 2015" [36], containing iris images collected from subjects wearing no lenses, soft (transparent) lenses, and textured (cosmetic) lenses. A number of 7200 images were used in the tests, with an equal number of samples (2400) for each of the three classes. A preprocessing step comprising contrast limited adaptive histogram equalization (CLAHE) enhancement [37] and iris segmentation was applied to all the images considered in the performed tests. CLAHE increases the contrast in the iris regions and makes the edges



(a) (b)

Fig. 1: Confusion matrices for the 3-class tests. (a): ViT-16; (b): Resnet-34 + CBAM.

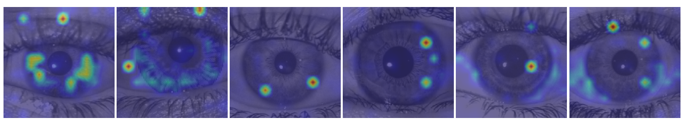


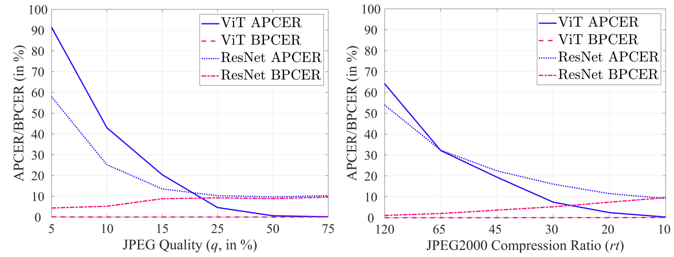
Fig. 2: Attention maps for original images: textured lenses in the first two columns on the left, no lenses in the two middle ones, soft lenses in the last two on the right.

more visible. Segmentation based on the Hough transform was employed to identify the iris region, given its potential positive effect on PAD [17]. The selected areas were incremented by 10%

A. ViT effectiveness for PAD

The used ViT-16 architecture was pre-trained on the ImageNet-1K dataset. For regularization purposes, its last linear layer was replaced by a combination of two linear layers interspersed with a dropout layer. Training was performed using cross-entropy as a loss function and stochastic gradient descent (SGD) as an optimizer, with batches of 128 samples.

Iris PAD performance was evaluated by computing the attack presentation classification error rate (APCER) and the bonafide presentation classification error rate (BPCER) [7]. To present generalizable results, instead of performing a single training/testing evaluation as in most studies [23], [24], a cross-validation approach was followed by carrying out five evaluations, each time taking 70% of the images in each class for training, 10% for validation, and 20% for testing. Moreover, training was conducted considering a 3-class scenario to distinguish each available class, and a binary training scenario where the "no lens" and "soft lens" classes are joined to represent bonafide images, whereas the "texture lens" class provides presentation attacks. The proposed ViT-16 network achieved an APCER = 0.1% and a BPCER = 0% in both the 3-class and binary training scenarios, with the confusion matrix associated with 3-class tests in Figure 1(a). In the challenging 3-class scenario, some images with soft lenses are misclassified as if no lens is present. Yet, all bonafide images are correctly interpreted, with only a few errors committed for textured iris in the whole cross-validation. For comparative purposes, analogous tests were conducted with a ResNet-34 network equipped with a convolutional block attention module



(a) (b)

Fig. 3: PAD performance for varying compression levels. (a): JPEG; (b): JPEG2000.

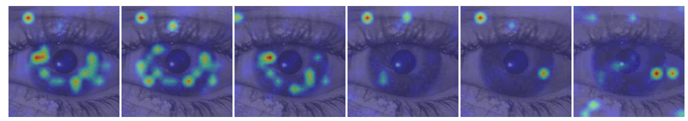


Fig. 4: Attention maps for increasing JPEG compression on textured iris images, with decreasing quality from left to right.

(CBAM) [24]. In this case, there is a notable difference in training with 2 or 3 classes, with the binary case resulting in an APCER = 4.4% and a BPCER = 2.9%, while the 3-class scenario in a much more significant variability across different iterations and an overall APCER = 11.7% and BPCER = 6.5%, with the corresponding confusion matrix in Figure 1(b). Besides providing consistently better results for PAD, the proposed ViT-16 thus also provides further details regarding the processed images, detecting also soft lenses.

The attention maps computed for samples from each of the 3 iris classes are given in Figure 2. The regions of interest change for each kind of input, with attention mostly put on the iris borders for images with soft lenses, on spots within the iris when no lens is present, and on distributed regions within the iris when textured lenses are worn. The obtained maps are fairly different from those obtained with general methods such as GradCAM since they are specific and inherently computed by the considered ViT, and directly drive the decisions when processing their inputs.

B. Effects of Compression

We evaluated the effects of lossy compression on recognition using the JPEG [38] and JPEG2000 [39] codecs provided by the ImageMagick library (v7.1.1-43). In particular, the JPEG quality factors (q) investigated were 5%, 10%, 15%, 25%, 50%, and 75%. For JPEG2000, we considered six different compression ratios (rt) between 10 and 120. The effects of compression on the achievable APCER and BPCER are shown in Figure 3. It can be seen that increasing compression mainly influences the capability to correctly recognize attack samples, with the APCER less affected, especially for the proposed ViT approach. The effects of JPEG compression on ViT attention maps are shown in Figure 4, where decreasing quality is applied to the original textured iris image at the far left of Figure 2, eventually leading to misclassification when the produced ViT maps become similar to those obtained for genuine samples.

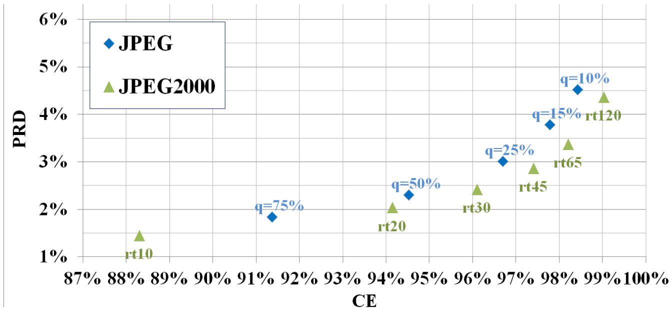


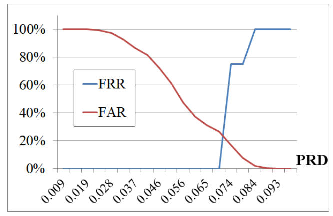
Fig. 5: Average compression efficiency (CE) and percentage root mean square difference (PRD) of JPEG and JPEG2000 for different values of the respective compression parameters.

A more detailed analysis is conducted by evaluating, for all compressed images, the Percentage Root-mean-square Difference (PRD), i.e., the distortion between original and compressed images in percentage [40], and the Compression Efficiency (CE) defined as CE $= \left(1 - \frac{B_c}{B_o}\right) \times 100$, being B_o and B_c respectively the sizes (in bytes) of the original and compressed images. The average CE and corresponding average PRD, evaluated on the whole image dataset for different values of q and rt, are shown in Fig. 5. Furthermore, the False Rejection Rate (FRR) and False Acceptance Rate (FAR) are used to compare recognition performance on compressed datasets against the original dataset. Specifically, FRR(x) represents the percentage of genuine samples with $PRD < x$ that are incorrectly rejected, while FAR(x) represents the percentage of fake samples, i.e., images with textured lenses, with $PRD > x$ that are incorrectly taken for genuine samples. Note that FRR measures how well the system can identify legitimate users for a given maximum amount of distortion.

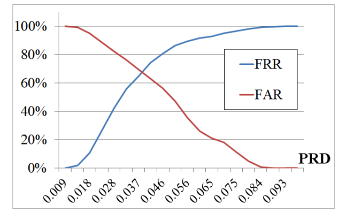
In Fig. 6, we report FRR and FAR curves evaluated for both JPEG and JPEG2000 lossy compression algorithms considering both ViT-16 and ResNet-34 classifiers for recognition. It is worth noting that results reported in Fig. 6 are based on tests carried out on 43,200 compressed images. As shown in Fig. 6.(a), in the case of JPEG compression and ViT-16 model, the FRR remains zero up to PRD = 7%. Instead, in the case of JPEG compression and the ResNet-34 model (see Fig. 6.(b)), the FRR is greater than zero even for minimal values of PRD, i.e., PRD $> 0.01\%$. These results further confirm the superiority of the ViT-16 system. Moreover, by comparing Fig. 6.(c) and Fig. 6.(a), it can be observed that a more significant distortion can be tolerated in the case of JPEG image compression compared to JPEG2000 compression. Finally, observing the set of FAR curves shows that impostors are correctly recognized if the PRD is maintained below 2%.

A more detailed analysis was conducted by further analyzing compression results, considering distinct image subsets corresponding to the different values of the compression parameters. In particular, we evaluated how compression parameters impact transparent (soft) lenses and textured (hard) lenses by analyzing the confusion matrices.

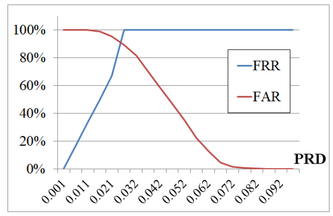
For space's sake, we consider only the case of JPEG compression and ViT-16 model. In Fig. 7 we show a few gray images representing confusion matrices achieved for different compression parameter values q. Note that the gray level reflects the number of images. In particular, white corresponds to the value 2400, i.e., the available number of images for each class. As shown in Fig. 7, images with no lenses (see the middle row in the confusion matrices) are marginally affected by the compression (in fact, the color of middle cells of all confusion matrices is white or very light gray for all values of q, so almost all "no lens" are correctly recognized as such). Textured lenses (see the top row in the confusion matrices) start to be misclassified as soft or "no lens" when $q \leq 25\%$. Instead, soft lenses (see bottom row in the confusion matrices) are misclassified even in the case of $q = 75\%$. Nevertheless, soft lenses are consistently misclassified as "no lens" and therefore correctly recognized as genuine samples, i.e., misclassifications of soft lenses as "no lens" has no impact on the recognition accuracy. Confusion matrices achieved with the JPEG2000 and ViT-16 model have similar trends, showing that textured lenses start to be misclassified as soft or "no lens" when $rt \geq 30\%$.



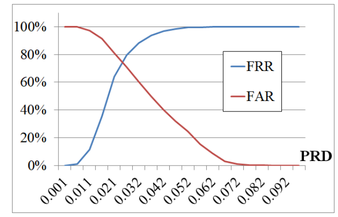
(a) FAR and FRR achieved with JPEG and ViT-16



(b) FAR and FRR achieved with JPEG and ResNet-34



(c) FAR and FRR achieved with JPEG2000 and ViT-16



(d) FAR and FRR achieved with JPEG2000 and ResNet-34

Fig. 6: FRR and FAR achieved with different models and compression algorithms.

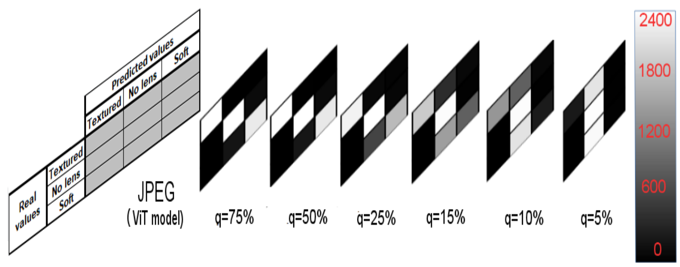


Fig. 7: Confusion matrices achieved with JPEG and ViT-16 model for decreasing values of q.

V. Conclusion

Iris PAD has been analyzed in this paper by evaluating the effectiveness of data-driven models relying on ViT architectures to distinguish bonafide samples from impostor attacks and investigating the effects of compression on the achievable recognition performance. The proposed approach has proven to be particularly effective for the desired task, providing the capability of recognizing also the presence of soft lenses in an iris image. The used ViTs give the tools to argue about the explainability of the decisions taken by analyzing the attention maps computed during processing the received inputs. The application of JPEG and JPEG2000 compressions has shown that the quality of the processed images cannot be decreased below certain levels to avoid incorrect interpretations, especially for fake samples.

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