

Generation of Non-Deterministic Synthetic Face Datasets Guided by Identity Priors

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Abstract. Enabling highly secure applications (such as border crossing) with face recognition requires extensive biometric performance tests through large scale data. However, using real face images raises concerns about privacy as the laws do not allow the images to be used for other purposes than originally intended. Using representative and subsets of face data can also lead to unwanted demographic biases and cause an imbalance in datasets. One possible solution to overcome these issues is to replace real face images with synthetically generated samples. While generating synthetic images has benefited from recent advancements in computer vision, generating multiple samples of the same synthetic identity resembling real-world variations is still unaddressed, i.e., mated samples. This work proposes a non-deterministic method for generating mated face images by exploiting the well-structured latent space of StyleGAN. Mated samples are generated by manipulating latent vectors, and more precisely, we exploit Principal Component Analysis (PCA) to define semantically meaningful directions in the latent space and control the similarity between the original and the mated samples using a pre-trained face recognition system. We create a new dataset of synthetic face images (SymFace) consisting of 77,034 samples including 25,919 synthetic IDs. Through our analysis using well-established face image quality metrics, we demonstrate the differences in the biometric quality of synthetic samples mimicking characteristics of real biometric data. The analysis and results thereof indicate the use of synthetic samples created using the proposed approach as a viable alternative to replacing real biometric data.

Keywords: Biometrics, Face recognition, Synthetic Face Image Generation, Deep learning, StyleGAN

1 Introduction

The popularity of biometric recognition has increased steadily along with the development of more accurate and convenient recognition technologies. According to ISO/IEC 2382-37:2017 [17], biometrics refers to the automated recognition of individuals based on their biological and behavioural characteristics. In particular, the human face has proven to be sufficiently unique and an easy-to-capture biometric characteristic, leading to a wide range of real-world applications, including border control, passport issuance, and civilian ID management. Driven by the promising performance of current face recognition systems, the Smart Borders program has been initiated



Fig. 1: Comparison of the intra-identity variation between FRGC v2.0 (top) and Sym-Face (bottom).

within the European Union to establish the Entry-Exit System (EES) [4], an automated IT system for registering travellers from third-countries, replacing the current system of manual stamping of passports. This system aims to help bona fide third-country nationals travel more easily while also identifying more efficiently over-stayers and cases of document and identity fraud. To perform automatically, EES will register the person’s name, type of the travel document and biometric data (face images and/or fingerprints).

A requirement for deploying biometric recognition at the European borders is complying with the high standards defined in the best practices for automated border control of the European Border and Coast Guard Agency (Frontex) [6]. The compliance with these guidelines must be validated by conducting large-scale biometric performance tests which require large datasets. As the collection of real face images is expensive, time-consuming, and privacy-concerning, generating synthetic face images has become an attractive and viable alternative. Driven by the advancements in technology, approaches like StyleGAN and StyleGAN2 [20][21] have shown promises to create large scale face datasets with unique identities.

While the synthetic image generation approaches are well used in various applications, the applicability of those images in biometrics is limited. Specifically, the biometric data used for training algorithms and performance testing need to mimic the real data with variations in pose, varying expressions, occlusions and illumination changes reflecting realistic conditions for any particular identity. In essence, each synthetic identity should accompany a set of variations that can compose what is referred to as mated samples for obtaining comparison scores. Specifically, the synthetic data should represent intra-class variations similar to bona fide data while preserving the identity information. The mated samples essentially are required to generate the genuine score distribution to gauge the biometric performance such as False Match Rate (FMR) and False Non-Match Rate (FNMR). However, despite the recent advancements of synthetic image generation [20][21], it continues to be a technical issue to create synthetic datasets with mated samples that are representative and comparable to real face images captured at border control scenarios (e.g. frontal head poses without face occlusions).

1.1 Our contributions

This work tackles the above-described challenge by introducing a new technique for generating synthetic mated samples. More precisely, a pre-trained StyleGAN generator [20] is utilised to generate synthetic face images of distinct synthetic individuals ("base images"). Each base image is represented by a latent vector $w_{1 \times 512}$, acting as a compressed version of the original image and reflecting the internal data representation learned by StyleGAN. Motivated by the idea of editing facial attributes by shifting the corresponding latent vector in a specific direction in the latent space [25], we propose to generate mated faces in a non-deterministic manner. We assert that such an approach for attribute editing leads to a better approximation of the natural intra-identity variation of bona fide mated samples, as can be compared in Figure 1.

As the components of the latent vector space can represent various possible semantics, the principal components can be interpreted as semantically meaningful directions in the latent space of StyleGAN. Concretely, extracting the Principal Components [22] from a latent vector space of 50,000 to 512 leads to obtaining semantically meaningful values. Inspired by such an argument, we create the mated samples by shifting the latent vectors into the directions given by the most relevant eigenvectors (i.e. the principal components). However, as the latent vectors are moved farther from their original locations, the risk of losing the identity information increases, we, therefore, employ a pre-trained face recognition system (FR) [5] to obtain the distance between the original and edited image dynamically to ensure the preservation of identity information from mated samples for the original identity used for editing. We refer to non-deterministic face editing as changing multiple semantics in an unsupervised manner, as opposed to controlled face editing, where specific facial attributes are chosen to be edited.

With such a rationale of our proposed approach, we create a new dataset of face images with synthetic identities and mated samples for each identity in this work which we refer to as Synthetic Mated Face Dataset (SymFace Dataset). The dataset consists of 77,034 samples with an average number of three mated samples per synthetic identity. To better approximate a semi-controlled capturing environment, images with extreme characteristics are sorted out, taking into account illumination conditions, head poses rotation and inter-eye distance. Also, the study concentrates on adult face images due to the limited training data available from young children and seniors. We refer to Figure 3 to get an impression of typical images filtered out by our filtering pipeline.

We further evaluate the quality of our proposed synthetic dataset by comparing its properties to real face images taken from FRGC v2.0 [23]. Among other approaches for conducting such an analysis, we translate the biometric quality of each image to a quality score between [0, 100] using Face Quality Assessment Algorithms (FQAAs) [19]. In this context, a high-quality score indicates that the corresponding biometric sample is well suited for biometric recognition. On the opposite, low-quality scores deteriorate the recognition accuracy due to the low quality of the input image. This understanding of biometric quality corresponds to the terminology specified by ISO/IEC 29794-1 [16], defining the utility of a biometric sample as the prediction of the biometric recognition performance. In this work, two FQAAs are used for estimating and comparing the biometric quality: FaceQnet v1 [11] and SER-FIQ [26]. At this point, the reader is referred to Section 2 to obtain a more detailed description of these methods.

In the rest of the paper, Section 2 summarises the conceptual ideas of generating synthetic face images and mated samples. Next, Section 3 provides a detailed description of the proposed PCA-FR-Guided sampling approach. Section 4 details the newly created SymFace Dataset, and finally, Section 5 gives an overview of the experimental results, followed by a conclusion about the key findings in Section 6.

2 Related Works

2.1 Synthetic Image Generation

In 2019, Karras et al. [20] presented a style-based generator architecture for generative adversarial networks (StyleGAN), capable of generating synthetic images with high resolutions (1024x1024) and realistic appearances. In addition to their proposed GAN architecture, the authors web crawled high-quality human face images from a social media platform (Flickr) to create a new dataset (FFHQ), covering a wide variation of soft biometrics.

Despite the recent success of deep generative networks, most generators are still operating as black-boxes and lack a deeper understanding of the latent space. To address these weaknesses and improve the disentanglement properties of the latent space, StyleGAN maps initially drawn latent vectors to an intermediate latent space, which turns out to encode facial features in a more disentangled manner. Further, Adaptive Instance Normalization (AdaIN) [13] enables to fuse the styles of different faces on multiple feature levels. Furthermore, stochastic variation is achieved by adding Gaussian noise to the feature maps after each convolution operation to vary fine-grained details. Recently, StyleGAN2 has been published by the same authors [21], improving the architectural design and fixing the characteristic artefacts occurring in the synthetic images generated by StyleGAN.

In StyleGAN and StyleGAN2, synthetic images are generated by randomly sampling from a known distribution (latent space). If these latent vectors are drawn from tail regions of the distribution, the quality of the generated face images deteriorates while the diversity of facial attributes increases. To balance this trade-off, a truncation factor can be used to stabilise the sampling: the truncated latent code w' is calculated as $w' = \bar{w} + \psi(w - \bar{w})$ where \bar{w} indicates the latent spaces' center of mass and ψ denotes the truncation factor. Following the empirical analysis of Zhang et al. [9], we choose a truncation factor of $\psi = 0.75$. In [9], the authors have shown that the biometric performance of synthetic samples generated with StyleGAN and StyleGAN2 are similar and comparable to bona fide images from FRGC v2.0 [23]. Hence, this work uses StyleGAN for generating synthetic base images to enable the implementation of PCA-FR-Guided sampling to operate within the framework of InterFaceGAN [25].

2.2 Mated Sample Generation

Though it has been shown in [9] that single synthetic face images can achieve comparable performances as bona fide samples for face recognition, mated samples are more commonly required in biometric performance evaluations. Given a synthetic base image, mated samples can be derived by editing facial attributes to simulate the factors of variation present in bona fide samples. With the groundbreaking work of Shen et al. [25], InterFaceGAN was introduced as a framework enabling editing facial attributes of synthetic identities through manipulating latent vectors in the latent space. In this context, the latent space reflects the internal data representation of

StyleGAN and structures various semantics learned from the training dataset. Further, the innovative architecture of StyleGAN significantly reduces the entanglement of the encoded semantics, which provides optimal conditions for controlled modifications on facial attributes.

The main contribution of InterFaceGAN is based on the observation that the latent space can be divided into linear subspaces according to binary semantics, such as "smile" or "no smile". Concretely, linear Support Vector Machines (SVMs) [3] are used to divide the latent space into subspaces for each facial attribute of interest. Once the SVMs are trained, facial attributes are modified by shifting the latent vectors into the perpendicular direction of the previously found boundaries, thereby causing continuous changes. The same principle has been adopted by Colbois et al. [2], who manipulate yaw angle, illumination, and a smile by approximating the bona fide conditions of Multi-PIE [7].

2.3 Limitations in State-of-the-art

Although InterFaceGAN generates visually appealing mated samples, their applicability for general biometric performance tests is still limited and understudied. As shown in Figure 1, mated samples collected in real-world scenarios naturally include several variations varying at the same time, for instance, pose, illumination, expression and a combination of them. In contrast, controlled face editing focuses on changing only a few semantics while leaving others fixed. Therefore, controlled modifications are useful to determine the vulnerability of face recognition systems for targeted semantics while only representing a small subset of the potential diversity in bona fide datasets. Motivated by this observation, we introduce PCA-FR-Guided sampling as a technique for generating non-deterministic mated samples to either replace or complement existing test datasets.

3 PCA-FR-Guided Sampling

This section introduces our new method for generating mated samples, which we refer to as PCA-FR-Guided Sampling. As described in Section 2, semantic modifications can be caused by moving latent vectors in the latent space. However, this approach still leaves two questions unanswered: 1) How to choose semantically meaningful directions? 2) How to choose the distance to preserve identities while maximising the intra-identity variation?

Aiming to find solutions for the aforementioned questions, Figure 2 provides an overview of the PCA-FR-Guided sampling technique. After generating an initial synthetic dataset with StyleGAN with a truncation factor of $\psi = 0.75$ (A), PCA is applied to extract semantically meaningful directions from the corresponding latent vectors (B). The idea is to extract the latent direction with the most variance, leading to effective variation after image generation. Finally, the latent vectors are moved along the principal component axes while adjusting the distance dynamically by measuring the similarity between the original and the shifted mated sample in a step-wise manner (C). Algorithm 1 provides a detailed workflow of the PCA-FR-Guided mated sample generation process proposed in this work.

We specifically employ *stepSize* and the verification *threshold* as controlling parameters to balance the trade-off between intra-class variation and identity-retaining factor for generated mated samples. In other words, increasing the comparison thresh-

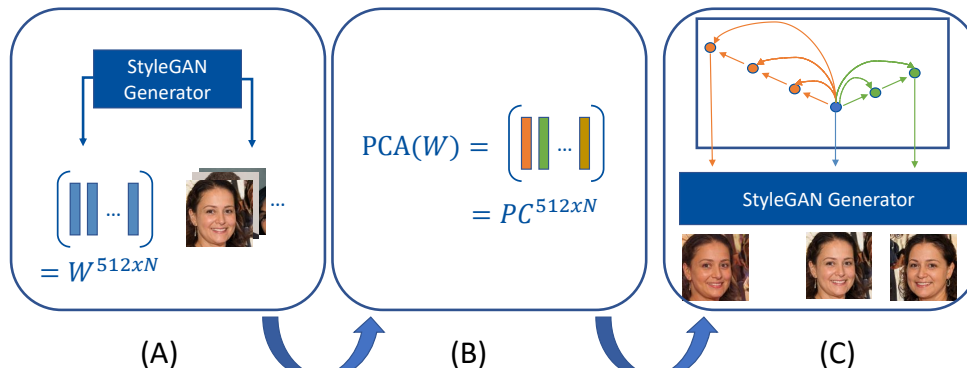


Fig. 2: Overview of the proposed PCA-FR-Guided Sampling with $N = 50,000$ denoting the number of latent vectors concatenated as matrix W to obtain the principal components (PCs). A detailed workflow is given in Algorithm 1.

old decreases the distance between the original latent vector and the shifted latent vector, thus generating more similar faces with fewer factors of variation. On the other hand, decreasing the step size approaches the given threshold with smaller steps, thus yielding mated samples closer to the desired similarity tolerance ³.

4 Synthetic Mated Face (SymFace) Dataset

This section describes the structure of our synthetic mated face dataset (SymFace) and the reference dataset used for the comparison part in Section 5.

Each mated sample is generated based on a synthetic face image randomly generated by StyleGAN. As StyleGAN was trained using images crawled from social media, the diversity of the generated images roughly corresponds to approximate capturing scenarios "in the wild". As described in section 2.1, a truncation factor of $\psi = 0.75$ was chosen to generate 50,000 unique identity images with high resolutions of 1024x1024 pixels and this is referred to as base images.

However, not all images generated from StyleGAN satisfy the minimum criteria needed for biometric applications. For instance, in a border-crossing scenario, factors such as minimum inter-eye distance (IED), illumination metrics, predicted head poses [1], and estimated ages [27] are needed in accordance to ISO/IEC TR 29794-5:2010 [15] and ICAO 9303 [14]. Accounting for this, we discard all such images not meeting the criteria of minimum inter-eye distance (IED), illumination metrics, predicted head poses [1], and estimated ages [27]. The SymFace Dataset thus has a total of 25,919 images which we deem as usable for further analysis in this work, and a sample of such images that are eliminated by our filtering pipeline is illustrated in Figure 3. As it can be observed from Figure 3, despite these images looking visually pleasing, they fail to meet the quality standards with respect to ISO/IEC TR 29794-5:2010 [15] and ICAO 9303 [14].

³ We have chosen $stepSize = 0.2$ and $threshold = 0.8$ empirically, considering the quality of the mated samples and the algorithm's efficiency. However, other values can also be used on application scenarios.

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input: latentVectors, N, stepSize, threshold, Generator
components = PCA(latentVectors);
for w in latentVectors do
    img = Generator(v);
    for c in components do
        i = 1;
        do
            w_moved = shift_in_lspace(w, c, stepSize · i);
            mated_img = Generator(w_moved);
            recognised = ArcFace(img, mated_img, threshold);
            i = i + 1;
            if recognised then
                | save(mated_img);
            while recognised;
        end
    end
end

```

Algorithm 1: PCA-FR-Guided sampling algorithm for generating mated-samples.



Fig. 3: Low quality images filtered out by our filtering pipeline - from left to right: IED, illumination, pitch angle, yaw angle, age.

Finally, the filtered base images are used as a basis for generating two mated samples for each synthetic identity by using our proposed PCA-FR-Guided sampling technique. Though we selected the first and second principal components, our experiments indicate that each of the 512 principal components can be used to obtain semantically meaningful mated samples. In addition, we apply InterFaceGAN to create three additional datasets, each of which includes mated samples with single semantics edited (yaw angle, illumination quality, and smile).

	SymFace	FRGC v2.0	Illumination Quality	Smile	Yaw
# Base Images	50,000	/	50,000	50,000	50,000
- Filtering	25,919	/	25,919	25,919	25,919
+ Mated Samples	77,757	24,025	77,757	77,757	77,757
- Filtering	77,034	17,919	74,183	74,574	60,504

Table 1: Dataset sizes in different development stages after applying our filtering pipeline and generating mated samples.

4.1 Reference Biometric Dataset

Further, we employ FRGC v2.0 [23] as a reference dataset, including 24,025 bona fide images captured in constrained conditions that resemble the image quality in a border-crossing scenario. Finally, we analyse biometric use cases of the SymFace dataset by studying the characteristics and comparing the same against the FRGC v2.0 dataset. A concise overview of the above-described datasets is given in Table 1, listing the number of samples counted during different development stages. Moreover, Figure 4 presents example images extracted from all datasets, annotated with quality scores obtained by SER-FIQ and FaceQnet v1.

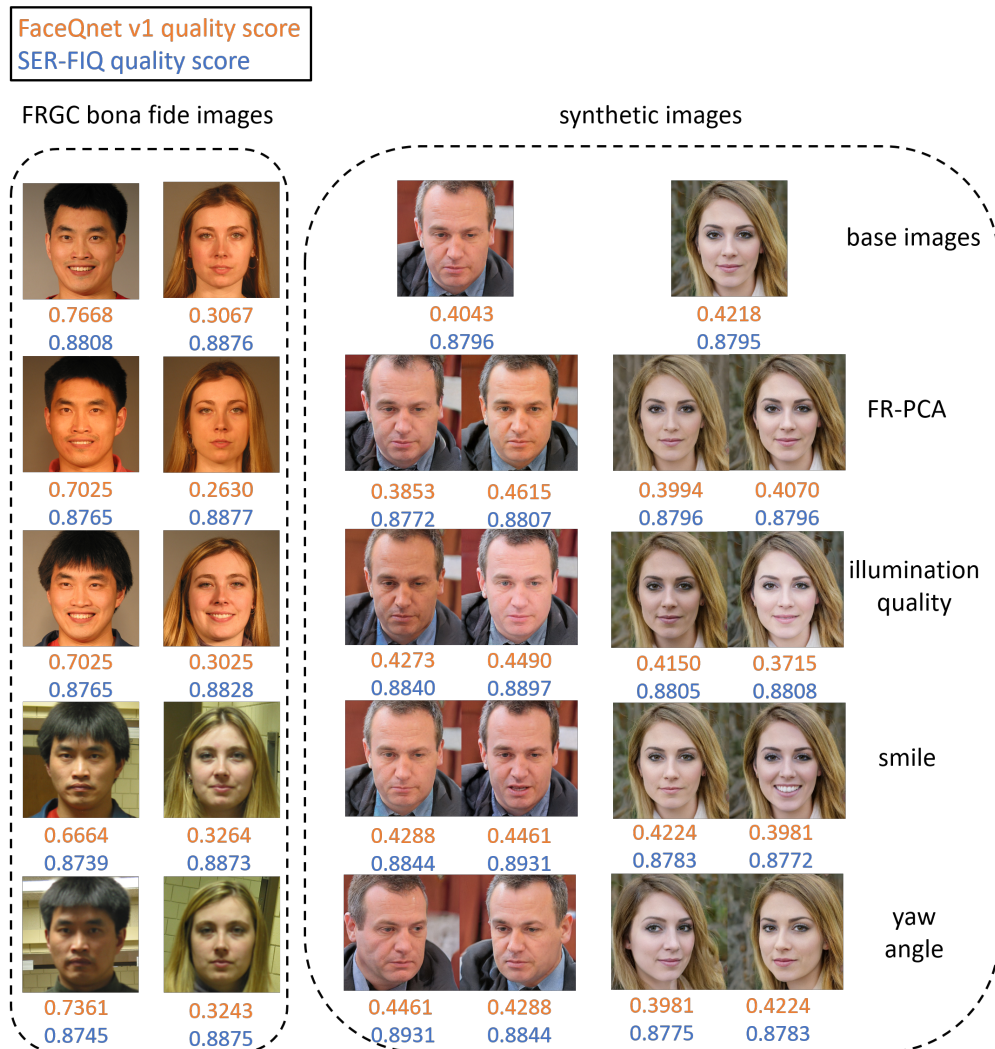


Fig. 4: Examples images of bona fide and synthetic images evaluated in Section 5.

5 Experimental Results

The biometric utility of the synthetic database, especially for mated samples, can be evaluated by measuring the biometric performance or by validating the quality of the samples according to well-established face image quality metrics. We employ both approaches by first evaluating the Face quality assessment algorithms (FQAAs) on the newly created SymFace Dataset and compare it against similar characteristics of the FRGC v2.0 dataset. We then evaluate the mated and non-mated comparison score distributions obtained by applying the pre-trained VGGFace2 [24] face recognition model to verify the biometric utility by analysing the score distribution. We provide a summary of the employed FQAAs for the convenience of the reader.

5.1 Face Image Quality Assessment

Face quality assessment algorithms (FQAAs) are used as indicators of how the quality of a face image contributes to the overall accuracy of a face recognition system. In this work, two representative FQAAs are utilised to evaluate the generated mated samples' biometric quality:

- **FaceQnet v1** is a deep learning-based FQAA proposed by Hernandez-Ortega et al. [11], aiming to predict the general utility of a face image, independent of a specific face recognition system. For the quality score prediction, a pre-trained network of ResNet-50 [10] is fine-tuned as a feature extractor on a small subset of the VGGFace2 dataset [24], including 300 subjects. FaceQnet v1 follows a supervised learning approach, which means that the ground truth quality scores are required for fine-tuning the model. However, finding representative quality scores that accurately reflect general utility criteria is a challenging task. Therefore, the authors propose to determine the utility of an image by comparing it to an ICAO 9303 [14] compliant image, knowing that the sample with unknown image quality can only cause low comparison scores. The performance of FaceQnet v1 has been benchmarked against other FQAAs and proven competitive in the ongoing quality assessment evaluation of the National Institute of Standards and Quality (NIST)[8].
- **SER-FIQ** [26] is an unsupervised technique that is not dependent on previously extracted ground truths for training a prediction model. Compared to FaceQnet v1, which outputs the general utility of a face image, SER-FIQ focuses on predicting the utility for a specific face recognition system. More precisely, the quality scores are based on the variations of face embeddings stemming from random subnetworks of a face recognition model. The authors argue that a high variation between the embeddings of the same sample functions as a robustness indication, which is assumed to be synonymous with image quality. The computational complexity of SER-FIQ increases quadratically with the number of random subnetworks, which leads to a trade-off between the efficiency of the algorithm and the expected accuracy of the quality predictions. In this work, we are following the authors' recommendation, choosing $N = 100$ stochastic embeddings. The comparison of the authors against state-of-the-art FQAA approaches indicates that SER-FIQ significantly outperformed alternative methods.

The distributions of the quality scores predicted with FaceQnet v1 and SER-FIQ are shown in Figure 5. On the left, the well-aligned curves indicate that the average

biometric quality across the evaluated datasets is nearly identical. However, looking at the SER-FIQ quality scores reveals a discrepancy between the distributions of the synthetic and bona fide images. We explain this observation with a wider range of yaw angles present in the synthetic datasets, a factor known by the authors of SER-FIQ to decrease the utility estimations [26]. The same behaviour is reflected by the left-shifted purple curve, thereby validating the negative impact of yaw angle variations on the biometric quality. Overall, the analysis of the utility scores does not reveal significant differences between bona fide and synthetic images. Moreover, except for yaw angle manipulations, these differences even vanish when comparing only synthetic datasets. Hence, the biometric quality of mated samples generated with PCA-FR-Guided sampling and InterFaceGAN are similar as both are products of the same generator. Further, the generation of mated samples has not deteriorated the biometric quality, as indicated by the overlapping areas to the base image distributions.

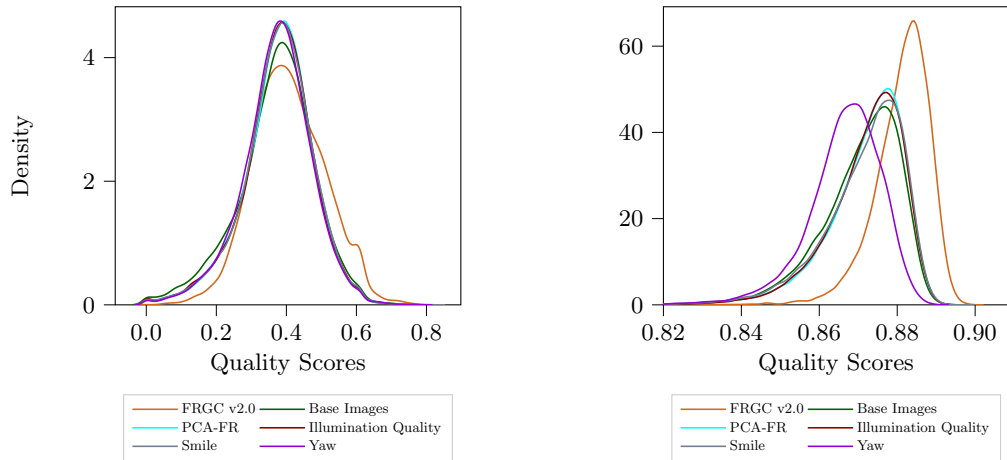


Fig. 5: Quality score distributions of two FQAAs: FaceQnet v1 (left) and SER-FIQ (right).

To further investigate the credibility of the FQAAs, Error-vs-Discard Characteristic (EDC) curves are shown in Figure 6. EDCs are commonly used to compare the performance of multiple FQAAs as suggested by the third version of ISO/IEC WD 29794-1:2021 [18]. For each face comparison, a paired quality score is defined as the minimum of the single quality scores predicted with the FQAAs. Finally, EDC curves are obtained by measuring the FNMRs by increasingly discarding the lowest quality images from the test set. Hence, decreasing EDC curves indicate lower misclassification rates; thus, the underlying FQAA could predict the biometric quality.

In Figure 6, all EDC curves share the same decreasing trend. However, the orange curves (FRGC v2.0) are steeper, indicating that both FQAAs are more accurate in predicting the biometric quality of bona fide images than synthetic samples. One reason for this observation might be rooted in an increased intra-identity variation of the

bona fide images, which is still challenging to mimic with synthetic substitutes. This assumption fits with the analysis of the mated comparison scores presented in the following subsection.

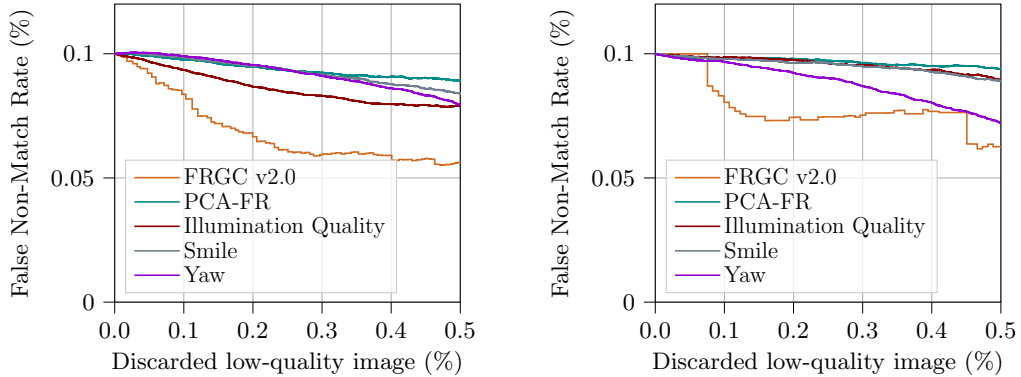


Fig. 6: EDC curves based on paired quality scores derived with FaceQnet v1 (left) and SER-FIQ (right). False non-match rates are computed with ArcFace [5].

5.2 Biometric Performance

After evaluating the biometric quality with dedicated FQAAs, the synthetic face images are further assessed in Figure 7, visualising the comparison score distributions. The non-mated comparison score distributions of all synthetic datasets are clearly below the vertically marked threshold, therefore indicating that the proportion of non-mated lookalikes is not significantly increased compared to non-mated bona fide samples. However, the mated comparison scores reveal more significant differences between the datasets. It is visible that the thick orange curve (FRGC v2.0) is heavier tailed on the left side than all synthetic mated distributions. Again, this observation re-validates the findings of the last subsection, tracing back the differences to a lower similarity of mated samples caused by varying facial attributes. Moreover, the mated comparison scores of the synthetic datasets reveal minor differences: While our proposed PCA-FR-Guided sampling performs similar to the controlled manipulation of smiles, editing yaw angles widens the span of mated comparison scores significantly. Overall, the well-separated distributions of mated and non-mated comparison scores lead us to conclude that either editing single (InterFaceGAN) or multiple (PCA-FR-Guided sampling) semantics can be promising for generating synthetic datasets for biometric performance tests. In addition, a quantitative analysis, measuring the Kullback-Leibler Divergences between the distributions presented in this section, is provided in Table 2 and Table 3 (appendix).

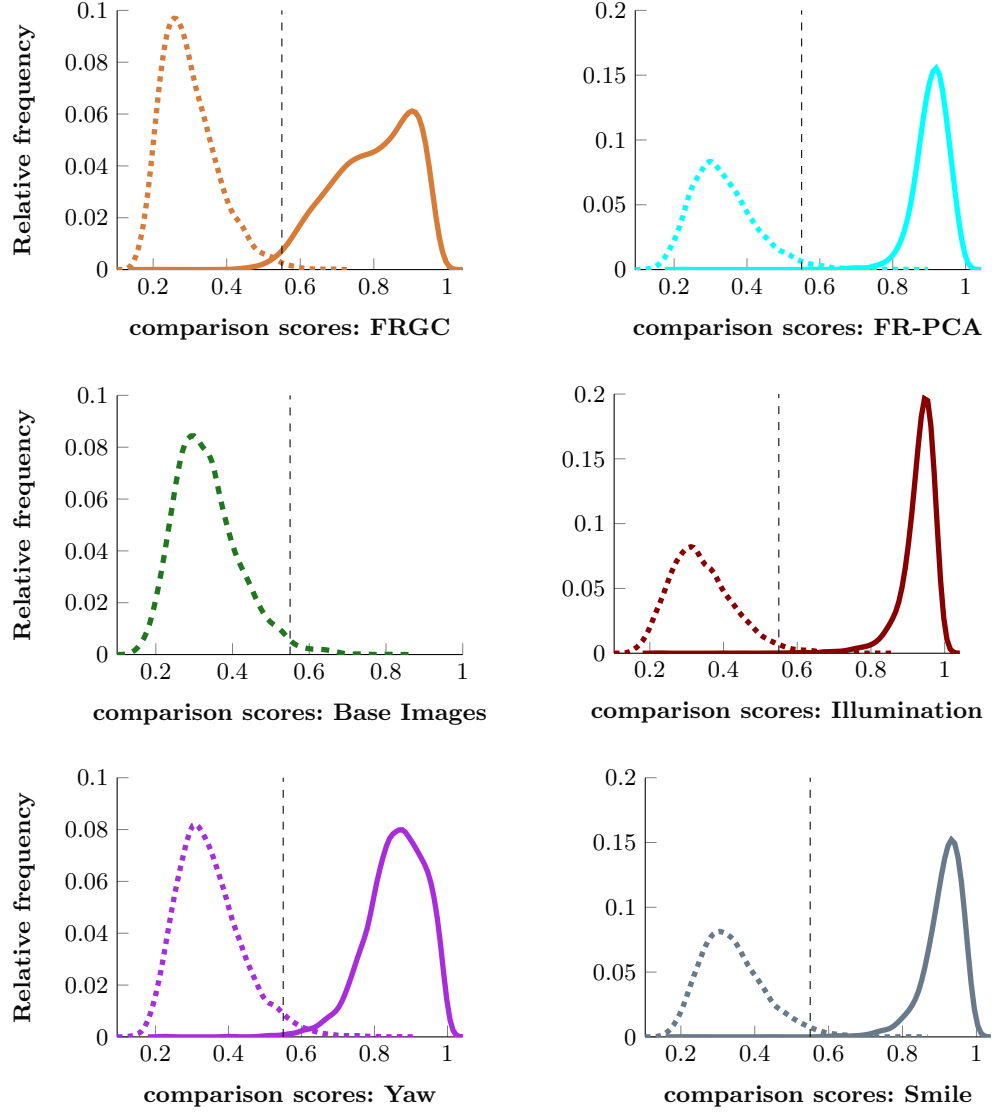


Fig. 7: Mated and non-mated comparison scores computed with VGGFace2 [24]. Thick solid line represents the kernel density curve of mated comparison scores, Thick dotted line represents the non-mated comparison scores and black dashed line represents the threshold @ FMR= 0.1% on LFW [12] dataset. Note that our base image dataset includes a single image per identity, therefore only depicting the non-mated comparison score distribution.

6 Conclusion and Future Work

To solve the privacy-related issue with real datasets and overcome the shortage of training data, we introduce PCA-FR-Guided sampling for generating mated samples in a non-deterministic manner. Unlike controlled face image editing techniques operating in the latent space, we apply PCA to find semantically meaningful directions. While moving latent vectors into these directions, the identity of the underlying face image is preserved by progressive supervision with a pre-trained face recognition system. With the newly created Synthetic Mated samples dataset (SymFace Dataset) with 77,034 images, we have evaluated state-of-the-art face quality assessment algorithms and biometric comparison score analysis to validate the applicability of the proposed approach. The well-separated distributions between mated and non-mated comparison scores indicate that synthetic mated samples generated with PCA-FR-Guided sampling are well suited for biometric performance tests. Furthermore, the analysis of face quality and the comparison scores is comparable to observations made in real datasets, indicating the usefulness of the proposed approach.

Although this work has illustrated to include synthetic samples in face recognition performance tests, we emphasise the open challenge to mimic the full extent of intra-identity variation measurable in bona fide datasets. Future works should also focus on an exploratory analysis of the different principal components, thereby exploring the latent space of StyleGAN and strengthening the understanding of the internal data representation. We foresee using the proposed approach to reduce the need for large training sets and minimise the demographic bias by diversifying latent space in synthetic generation schemes.

Appendix

Datasets		PCA-FR	Illumination Quality	Smile	Yaw
FRGC v2.0	SER-FIQ	1.17	1.19	1.13	3.25
	FaceQnet v1	0.11	0.12	0.11	0.13
Base Images	SER-FIQ	0.02	0.01	0.01	0.27
	FaceQnet v1	0.01	0.01	0.01	0.01

Table 2: KL-Divergences between quality score distributions in Figure 5.

Datasets		PCA-FR	Illumination Quality	Smile	Yaw
FRGC v2.0	Mated	0.42	0.79	0.17	0.72
	Non-mated	0.27	0.28	0.32	0.33
Base Images	Mated	/	/	/	/
	Non-mated	0.01	0.20	0.02	0.01

Table 3: KL-Divergences between comparison score distributions in Figure 7.

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