Evolutionary latent space search for driving human portrait generation

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Abstract—This article presents an evolutionary approach for synthetic human portraits generation based on the latent space exploration of a generative adversarial network. The idea is to produce different human face images very similar to a given target portrait. The approach applies StyleGAN2 for portrait generation and FaceNet for face similarity evaluation. The evolutionary search is based on exploring the real-coded latent space of StyleGAN2. The main results over both synthetic and real images indicate that the proposed approach generates accurate and diverse solutions, which represent realistic human portraits. The proposed research can contribute to improving the security of face recognition systems.

Index Terms—generative adversarial networks, evolutionary algorithms, latent space exploration, human portraits generation
I. INTRODUCTION

Generative Adversarial Networks (GANs) are machine learning methods to learn generative models [1]. Generative models take a training dataset drawn from a specific distribution and learn to represent an estimate of that distribution.

GANs consist of two artificial neural networks (ANNs): a generative model (generator) and a discriminative model (discriminator), which apply adversarial learning to optimize their parameters. The generator $g$ learns how to transform input vectors from a random latent space $z$ into “fake” samples $x'$, i.e., $g(z) = x'$, that approximate the true data distribution. Simultaneously, the discriminator learns to distinguish the “real” samples from the training dataset $x$, from the ones produced by the generator $x'$. GAN training converges to an optimal generator that approximates the real distribution so well that it deceives the discriminator, which randomly labels real and fake samples.

GANs have demonstrated being a successful tool for many applications that require the creation of synthesized data, especially those concerning multimedia data (e.g., images, sound, and video), healthcare, and other areas [2]–[5].

In general, the fake sample produced by the generator is determined by the latent space vector read. This latent space to produce the samples in a GAN is generally defined by a high dimensional random distribution, e.g., Gaussian distribution, linked to the trained generative model.

This article presents a proposal for finding a sub-latent space (i.e., vectors from the latent space) that produces fake samples that meet given criteria. Specifically, on the basis of a GAN pre-trained to produce realistic human face images, the proposed research aims at finding latent space vectors that make that GAN to produce human portraits with specific attributes. In this case, the target human face images to create should be similar to a given target human portrait to the human eye. The large search space defined by the latent space makes impractical the use of traditional optimization methods for this purpose (e.g., enumeration techniques, backtracking or dynamic programming). Thus, heuristic and metaheuristics [6] are useful methods to perform the search using bounded computational resources.

Thus, in the proposed research, an evolutionary algorithm (EA) is applied to search the latent space for vectors. StyleGAN, a well-known GAN pre-trained to randomly create realistic human face images [7], is the one used to generate the tentative samples (human face images). FaceNet [8], an ANN pre-trained to extract the main features of human face images, is employed to evaluate the generated samples and guide the EA during the evolutionary process. Therefore, the FaceNet output is applied to compute the distance between the target human face image and the generated one.

FaceNet is widely used by face recognition systems [9]. One of the main aims of this research is to synthetically create different human face images that according to FaceNet belong to the same person. Thus, the proposed approach is useful to create adversarial samples able to deceive face recognition systems based on ANN. This research line can contribute to improve the security of face recognition systems.

This work addresses the capability of generative models to produce samples from the whole data distribution (i.e., create any human face image) and the usefulness of EAs to perform an efficient search of the latent space. The main contributions of this article are: i) a method based on EAs to generate synthesized human portraits to be similar to a given target face, which could be used to deceive face recognition systems, ii) the analysis the efficacy of the proposed approach when dealing with different types of target human faces, and iii) the analysis of its computational cost.

The article is organized as follows. Next section introduces the problem of exploring the latent space for portrait generation. Section III describes the methodology and Section IV presents the proposed EA for the problem. The experimental analysis is reported in Section V. Finally, Section VI presents the conclusions and the main lines for future work.

II. EXPLORING LATENT SPACE FOR FACE GENERATION

This section describes the problem of exploring the latent space of GANs for generating faces and reviews relevant related works.

A. Latent space exploration

Most of the research on GANs aims at improving their reliability and the accuracy of the trained generative models (i.e., generators). Lately, few studies have been focused on the latent space, which is unique for each generator and eventually determines its produced samples. Generally, the generator produces an output (e.g., an image) by randomly sampling the latent space distribution, i.e., by taking a random vector from the latent space. The latent space is defined by a high dimensional random distribution called the prior. This article focuses on the latent space exploration problem, which consists in finding the sub-spaces of the latent space (or computing vectors from the prior) for forcing a given generator to produce a specific output (i.e., samples that meet certain criteria).

Specifically, the proposed research addresses the latent space exploration of a given pre-trained generator (StyleGAN) for creating human face images similar to a target portrait. Due to the high dimensionality of the latent space, the search was carried out by using an EA. The sample produced by StyleGAN is evaluated by FaceNet, another pre-trained ANN, which evaluates the similarity between the produced sample and the target portrait. The output computed by FaceNet is used to guide the EA search through the latent space.

B. Related work

The Latent Variable Evolution (LVE) approach was originally proposed for the generation of fingerprints [10], using metaheuristics to optimize an ad-hoc quality metric. Non-evolutionary approaches have also been applied to explore the latent space of GANs. For example, models based on Generative Kernel Principal Component Analysis allow for the
interpretation of components by moving in the feature space, thus providing an insight into the underlying latent space [11].

Focusing on human face images, Fernández et al. [12] applied EAs to search the latent space to improve the diversity of samples generated by an unsupervised GAN. A genetic algorithm and a Map Elites method were used to evolve solutions that represent a set of 50 latent space vectors to generate 50 images. The fitness function was evaluated in terms of the diversity of the produced faces.

StyleGAN was proposed as an improvement over deep convolutional GANs, a model where the generator embeds the input latent vector into an intermediate latent space, which has an important effect on how the variation factors are represented in the ANN [7]. StyleGAN automatically learns the separation of high-level attributes (e.g., pose and identity) and the stochastic variation in the generated images (e.g., hair). It allows smooth interpolation and style mixing with high quality output images.

Shen et al. [13] proposed InterFaceGAN for semantic face editing by interpreting the latent semantics learned by GANs, and studied how different synthetic face semantics are encoded in the latent space. InterFaceGAN finds hyperplanes that divide the latent space in subregions that generate specific attributes. By leveraging those regions, InterFaceGAN manipulates in an isolated manner facial attributes for gender, age, presence of eyeglasses, smile, and pose on images generated by StyleGAN.

The StyleGAN2 Distillation architecture was proposed to change the facial features of gender and age, and to perform style transfer and image morphing [14]. The distillation allows extracting the appearance information from the generated faces and provides a way to manipulate these attributes.

All reviewed works trained their own architecture and focused on the exploration of the latent space to modify specific facial attributes (gender, age, pose, etc.). In contrast, the approach proposed in this article does not require to train any new ANN model and leverages on the use of pre-trained models for both, generation and evaluation of the images. Additionally, the main goal is to generate faces that are similar to a given one, being able to deceive the model used to evaluate the similarity between the samples.

III. METHODOLOGY FOR AUTOMATIC GENERATION OF HUMAN FACES

A specific methodology is proposed for the automatic generation of human face images, with the main goals of generating high-quality, similar to the target face, but also with diversity while maintaining the main features of the target face. An hybrid methodology is applied, combining an EA and two pre-trained ANN models: a GAN to generate the images and a facial recognition model to assess the quality and diversity of generated images.

A population of latent vectors is evolved, which are given as input to a generative model to synthesize human face images. The search is guided by a quality indicator provided by another ANN model, that indicates the similarity of generated faces to the target image.

StyleGAN2 [7], a state-of-the-art GAN for face generation, is used as generative model. The model was pre-trained on the Flickr-Faces-HQ Dataset by NVIDIA. StyleGAN2 provides higher resolution image generation and the disentanglement of the latent space, which allows style mixing and smooth interpolation.

In turn, the quality of images is assessed using FaceNet [8], a well-known face recognition model that transforms a face image into data points in a high dimensional space, i.e., a vector of 128 continuous values for each input image. The output vectors of different input images, which belong to the same face, have the property of being geometrically close to each other. Thus, FaceNet is used to assess the resemblance of the generated faces to the target face.

Fig. 1 describes the modules integrated in the proposed system and their interactions.

IV. AN EVOLUTIONARY ALGORITHM FOR LATENT SPACE EXPLORATION

This section describes the proposed EA for exploring the latent space of GANs applied to realistic portrait generation.

1) Solution encoding: The applied solution encoding considers a vector of 512 floating point numbers, representing the components of the latent vectors in the StyleGAN2 space [7]. Values in the latent space during the training of StyleGAN2 were sampled from a standard normal distribution.

2) Fitness function: The fitness function evaluates the similarity of the target face to the face generated by StyleGAN2 using the individual as input. Embeddings, which represent the main features of a human face image, are used characterize the face generated. These embeddings are obtained by a forward pass through the facial recognition model, as described in Fig. 1. The fitness value of an individual is the opposite of the Euclidean distance (L2 norm) of the generated face embeddings to the target image embeddings. An initial implementation considering the evaluation of one individual at a time resulted in a very inefficient search procedure, mainly due to the significant inference times of the used ANNs when batch processing capabilities are not used. In order to improve the computational efficiency of the proposed EA, a parallel model for evaluation using batches was implemented.

3) Evolutionary operators: The proposed evolutionary operators are described next.

a) Initialization: A random initialization operator was applied. Each value in a solution encoding is generated according to a normal distribution $\mathcal{N}(0, 1)$. Seeding the population is a valuable idea in order to guide the search towards specific regions of the space, thus promoting certain features in the generated faces. This alternative is proposed as one of the main lines for future work.

b) Selection: The tournament selection was applied, which provides a good selection pressure to guarantee diversity during the search. Three individuals participate in the tourna-
ment, and one survives. This parameterization was determined in preliminary calibration experiments.

c) Recombination: The blend-alpha crossover operator (BLX-$\alpha$) [15] was applied, mainly because its search pattern adapts to the latent space exploration. The main idea is to properly exploit the intervals determined by values encoded in both parents and not focusing on simple combinations of encoded values. BLX-$\alpha$ uniformly selects values between two points that contain the two parents, but may extend equally on either side determined by the $\alpha$ parameter. This is a common procedure in real-encoding EAs to solve different problems. In preliminary calibration experiments, BLX-$\alpha$ allowed the proposed EA to compute better results than standard crossover operators. The value of $\alpha$ must be set to guarantee a proper exploitation of solutions. This procedure is often performed empirically. Fig. 2 presents examples of the phenotypes resulting of the application of the proposed recombination operator.

d) Mutation: Several mutation operators were studied in preliminary experiments to determine a proper means to introduce diversity in the search. The best results were obtained applying a Gaussian mutation with mean $\mu = 0$ and standard deviation $\sigma = 1$, which empirically showed to generate appropriate diversity without being too disruptive. Fig. 3 presents some examples of the phenotypes resulting of the application of the proposed mutation operator.

4) Implementation details: The proposed EA was implemented in Python 3.7 using the DEAP library version 1.3.1. Several improvements were implemented to accelerate the fitness evaluation process, including:

A Batch fitness evaluation. By default, the fitness evaluation in DEAP is performed sequentially, i.e., one individual at a time, mapping the fitness function to the list that holds the population. This procedure demands a large computation time when working with large ANNs. In order to speed up the fitness evaluation, both the face generation and the face recognition models can be executed in batches. This is a common technique when dealing with complex evaluation functions in EAs [16]. The
source code of DEAP was modified to exploit batching capabilities, for evaluating the entire population at once. The batch partitioning is left to the particular settings of each model.

B Image size reduction. The facial recognition model was trained on images of size 160×160 pixels. In consequence, when computing the fitness function, all generated images (1024×1024 pixels) were downscaled before detection, alignment, and embeddings generation, yielding a significant acceleration of the fitness evaluation process. The size reduction was applied only in the fitness calculations. Thus, the final output preserves its full resolution.

C Replacement of the face detection algorithm. The facial recognition model requires a tight crop to work properly. For this purpose, a Multitask Cascaded Convolutional Network (MTCNN) [17] was used. A preliminary validation analysis detected that, when applied to images generated by StyleGAN2, the coordinates of the bounding boxes returned by MTCNN do not vary significantly. This hypothesis was confirmed in experiments that analyzed 10,000 generated images: results demonstrated that the average interquartile range of the bounding box coordinates was 8 pixels (below 4% of deviation). Thus, instead of using MTCNN to crop the faces, a fixed average bounding box was used, removing the detection step from the fitness calculations, and further reducing the execution times.

V. EXPERIMENTAL ANALYSIS

This section reports the experimental evaluation of the proposed evolutionary search of the latent space in terms of the quality and diversity of the generated images, and the computational efficiency of the search. These experiments were performed on the Colaboratory platform from Google (colab.research.google.com/).

A. Problem instances

Six problem instances were taken into account by using the six different target human portraits shown in Fig. 4: G1, W1, and M1 were used for parameter setting experiments and G2, W2, and W3 validation experiments.

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B. Parameters setting experiments

Parameters setting experiments were performed on problem instances G1, M1, and W1 to find the most appropriate configuration of the recombination (p_R) and mutation (p_M) probabilities. The population size (200 individuals) and the number of generations (500) were established in previous experiments. Considered candidate values were p_R ∈ {0.6, 0.75, 0.9} and p_M ∈ {0.001, 0.01, 0.1}. The nine combinations of candidate values were studied, performing 30 independent executions of each parameter configuration for the considered instances.

C. Validation results

This subsection reports and discusses the results of the 30 independent executions of the proposed EA configured according to the results of the parameters settings experiments (i.e., population size = 200, number of generations = 500, p_R = 0.75, p_M = 0.001, α = 0.2). Four aspects are analyzed in validation experiments: the fitness results and its evolution, the computational cost of the proposed EA, and the quality and diversity of the generated face images.

Fitness values. Table I reports the minimum, mean, and standard deviation of the computed distances (opposite fitness values, i.e., lower values are better). For the three instances, the EA converged to lower values than the ones computed during the parameter setting experiments. When comparing the results of the three instances, the proposed approach provides better results when dealing with synthesized target images, i.e., G2, than when dealing with real ones. Fig. 4 illustrates the evolution of the minimum distance between the generated images and the target face (opposite fitness values) of ten independent runs for instance W2.

Fig. 4. Instances used in configuration experiments (top: G1, W1 and M1) and validation experiments (bottom: G2, W2 and W3).

| instance | distance | execution time (s) |
|----------|----------|-------------------|
| G2       | 0.350    | 614 ± 0.041       |
| W2       | 0.550    | 630 ± 0.049       |
| W3       | 0.420    | 896 ± 0.041       |

Computational cost. Table I also reports the execution times (minimum, mean, and standard deviation) of the proposed EA. The execution times of the optimized implementation were approximately seven times faster than the initial implementation without the improvements to accelerate the fitness function calculation. The proposed approach was able to
compute accurate images (close to the target) in less than 15 minutes, showing the main advantage of using a pre-trained model: there is no need of training complex ANN models (that imply high computational costs) to get competitive results. The larger execution times for W3 are directly related to the hardware allocation mechanism of Google Colab, which randomly chooses between different types of hardware instances.

Solution quality. The quality of results was evaluated according to the capability of the proposed method to deceive FaceNet. The rationale behind the proposed evaluation methodology is to compare the embeddings provided by FaceNet to the best generated image shown in Fig. 6 and to a different image of the same target person.

Table II reports the comparison of the computed embeddings with FaceNet for instances G2, W2, and W3, considering the $L_2$ distance as relevant indicator. As stated, the baseline result is the $L_2$ distance between the embeddings of the target image and another image of the same target person. For both instances, the distance between the synthesized image and the target one is shorter than the baseline value (up to 27.9% of reduction was achieved for problem instance W3).

The reported results show that the proposed method was able to deceive the facial recognition model, generating synthetic faces that produce embeddings closer to those of the target person than the embeddings obtained from a different image of the same person.

### Table II
| instance | target vs. fake | baseline | $\Delta$ |
|----------|----------------|----------|---------|
| G2       | 0.350          | *        | *       |
| W2       | 0.550          | 0.679    | 12.9%   |
| W3       | 0.420          | 0.583    | 27.9%   |

Diversity. To evaluate the diversity of the generated images, Table III reports the pairwise $L_2$ distances between the embeddings of the ten solutions found for each studied instance. Results suggest a proper robustness of the proposed method. In turn, the heatmap in Fig. 7 presents a representative example of the distances compute for ten solutions of the validation instance W2. Similar results were computed for the other studied validation instances.

### Table III
| instance | min   | max   | mean ± std |
|----------|-------|-------|------------|
| G2       | 0.314 | 0.599 | 0.491 ± 0.060 |
| W2       | 0.482 | 0.865 | 0.645 ± 0.099 |
| W3       | 0.401 | 0.674 | 0.544 ± 0.070 |

Fig. 6. Validation instances (top: G2, W2 and W3) and their associated best solution found in the validation experiments (bottom: SG2, SW2 and SW3).

Table [II] reports the comparison of the computed embeddings with FaceNet for instances G2, W2, and W3, considering the $L_2$ distance as relevant indicator. As stated, the baseline result is the $L_2$ distance between the embeddings of the target image and another image of the same target person. For both instances, the distance between the synthesized image and the target one is shorter than the baseline value (up to 27.9% of reduction was achieved for problem instance W3).

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Fig. 7. Pairwise distances for ten solutions for validation instance W2.
The obtained diversity in the computed results is a remarkable feature of the proposed method. It shows the capability of the evolutionary approach to explore the high dimensional latent space in such a way to provide a number of different samples that meets the defined criteria, i.e., it can provide diverse human faces that can deceive the base facial recognition model.

VI. CONCLUSIONS

This article presented an evolutionary approach for synthetic human faces generation based on the GAN latent space exploration. A specific methodology was proposed to produce human portraits close to a target one (i.e., with specific attributes), by using a pre-trained StyleGAN generator. A specific EA was implemented to explore the latent space, which used a face recognition model, FaceNet, to guide the search. In turn, several improvements were included in order to speed up the search.

The main experimental results indicate that the proposed EA was able to generate accurate face images. The capability of the proposed method to deceive FaceNet, the ANN used for similarity evaluation on most of the face recognition systems, was confirmed by the reduced distance between the synthesized image and the target one, which improved up to 27.9% the baseline result (a different image of the same target person). Diversity results suggest a proper robustness of the proposed method, which was capable of providing a set of different face images similar to the target one.

The main lines for future work are related to exploring strategies for guiding the search via population seeding or ad-hoc evolutionary operators to generate images with specific characteristics and analyze the capabilities of the proposed method to deceive automatic detection tools as suggested by the quality results.

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