Disentangling in Latent Space by Harnessing a Pretrained Generator

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Abstract

Learning disentangled representations of data is a fundamental problem in artificial intelligence. Specifically, disentangled latent representations allow generative models to control and compose the disentangled factors in the synthesis process. Current methods, however, require extensive supervision and training, or instead, noticeably compromise quality. In this paper, we present a method that learns how to represent data in a disentangled way, with minimal supervision, manifested solely using available pre-trained networks. Our key insight is to decouple the processes of disentanglement and synthesis, by employing a leading pre-trained unconditional image generator, such as StyleGAN. By learning to map into its latent space, we leverage both its state-of-the-art quality generative power, and its rich and expressive latent space, without the burden of training it.

We demonstrate our approach on the complex and high dimensional domain of human heads. We evaluate our method qualitatively and quantitatively, and exhibit its success with de-identification operations and with temporal identity coherency in image sequences. Through this extensive experimentation, we show that our method successfully disentangles identity from other facial attributes, surpassing existing methods, even though they require more training and supervision.

1 Introduction

Since the dawn of machine learning, learning a disentangled representation has been one of its core problems. Disentanglement can be defined as the ability to control a single factor, or feature, without affecting other ones [41]. A properly disentangled representation can benefit semantic data mixing [30, 62], transfer learning for downstream tasks [6, 60], or even interpretability [33]. Achieving disentanglement, however, is a notoriously difficult task, which has been addressed by many approaches.

A key challenge to learning a disentangled representation is reducing supervision. Similarly, to many other learning-related objectives, fully supervised solutions are most effective [2, 50], but impose often infeasible data collection requirements. It is not tractable, for example, to find a data set of paintings depicting the same scenes in different styles. The opposite approach, of a completely unsupervised disentanglement, is equally impractical at the moment, as it typically struggles with producing satisfying results [44]. Therefore, middle ground forms of supervision have been proposed. A prominent example is class-supervision, where only the feature of interest is labeled throughout the dataset, partitioning it into classes. The class-supervised setting assumes the existence of multiple samples in each class, and that the intra-class variation of this feature is significantly lower than the the inter-class ones [18]. While being more feasible, this approach still requires meticulous gathering.
Figure 1: Our disentanglement framework uses two encoders (left) to generate the latent code $$z$$, consisting of a description of the property of interest ($$f$$), and all the rest ($$\bar{f}$$). The code is then mapped to the latent space $$\mathcal{W}$$ of the employed pre-trained generator $$G$$. This decouples the tasks of learning quality image generation and disentanglement.

and labeling of data. Avoiding the labeling requirement would enable using virtually endless amounts of data.

In this paper, we present a novel method to disentangle a single feature from all other attributes, using no data specific supervision. In our case, supervision is solely realized through the use of relevant pre-trained networks — a plausible prerequisite, as shall soon be demonstrated, especially since these networks need not be trained on the same dataset or for the same task. Our key idea is to directly map the disentangled latent representation to the latent space of a pre-trained generator, as depicted in Figure 1. Given an a feature of interest $$f$$, we propose training two encoders, as is commonly done in disentanglement settings, $$E_f$$ and $$E_{\bar{f}}$$, seeking to encode only $$f$$, and everything but $$f$$, respectively. Unlike traditional methods, however, we then propose to map the resulting latent code $$z$$ to the latent space $$\mathcal{W}$$ of a powerful, pre-trained generator $$G$$, and assess the quality of the disentanglement only on the latter’s output. This mapping is the heart of our approach. It allows us to use a state-of-the-art pre-trained generator, inheriting its high-quality and fidelity, and to control its output in a disentangled manner with minimal training. Furthermore, our approach relaxes the requirement for a distinct disentanglement, where the representation is split into two parts that carry completely separate information, since the mapping is trained to extract only the required information from each part. In practice, this approach decouples the disentanglement task from the synthesis one, allowing the native employment of the most expressive and high-quality image generation techniques, and a dedicated training process for content control without compromising generation quality.

We demonstrate our approach using arguably the most powerful unconditional image generator available nowadays — StyleGAN [31], in one of the most challenging image generation domains — the human face and head. Generating and manipulating faces is highly applicable on one hand, but is also known to be particularly hard, on the other. Besides the challenges of dealing with human faces that arise from the keen human perception of them [45], and their high photometric, geometric and kinematic complexities, the human face has many independent, high dimensional attributes. From these, we chose to demonstrate image synthesis with disentangled control over the person identity attribute, as illustrated in Figure 2. This type of control is useful in applications such as de-identification, reenactment, and many others. Unlike other methods [18, 7, 22, 16], our training data does not contain examples of the same person twice, nor does it have any indication or labeling regarding the person’s identity. Through the use of available networks for evaluating identity and facial landmarks, our approach effectively transforms StyleGAN into a conditional image generator, conditioned on either the identity of the person or all other facial attributes, such as expression, pose and illumination.

As we shall see, the performance of our disentangled image generation heavily depends on the capabilities of the selected generator. In the case of StyleGAN, this means phenomenal image quality, outperforming all previous disentangled control attempts we compare to, but at the cost of expressiveness, as some of the faces do not reside within the attainable domain of the generator, due
Figure 2: Sample results generated by our method, demonstrating the ability to disentangle identity from other facial attributes: pose, expression and illumination and preserving one while manipulating the other. Three images are used as input, forming a 3 by 3 table combinations generated by our method. As can be seen, identity is preserved along the columns, and attributes are preserved along rows.

to the data used during its training. Nevertheless, in addition to superior quality, our method also successfully handles the generation of the entire head, including the hair — a region that is known to have a strong impact on identity [3]. This is in contrast to state-of-the-art methods, which manipulate facial features only [5, 36, 46, 19].

As validation, we offer several experiments, evaluating qualitatively and quantitatively face identity and attributes manipulations, and compare them to previous methods. The experiments assess feature combination, de-identification operations, and temporal coherency of identity over sequences. The methods we compare to include state-of-the-art class-supervised disentanglement methods, which rely on a more structured, better labeled, but harder to curate, data. We evaluate all methods in terms of the quality of disentanglement and preservation of composing factors on unseen faces, as well as image quality and diversity. Our method is shown to outperform previous art, in addition to offering unique advantages, such as the said generation of the entire head and hair, and minimal supervision, which does not necessitate multiple images of the same person at any point.

2 Related work

Disentanglement. Many works learn disentangled representations and use various levels of supervision. Fully supervised methods [2, 50] learn from a dataset in which all relevant underlying factors are labeled. In this case, a sample from the dataset takes the form of (input, transformation, result of transformation). Critically, a ground truth is available for any transformation performed on the data. This data requirement is infeasible in many domains and tasks. On the other end of the spectrum,
fully unsupervised methods [27, 33, 9] learn from a dataset with no associated information. These methods employ information-theoretic regularization losses to encourage disentanglement. These methods trade-off quality for disentanglement, often explicitly [27, 33], and thus produce low visual quality results. Class-supervised methods [18, 7, 22, 16, 62] use additional labels that partition the images to classes, defined by a set of mutually exclusive attribute values. For example, each class contains a set of images of a single identity only, while other attributes vary. In contrast, we examine a more challenging but easily attainable dataset, in which no person appears twice, and no labeling is offered.

**Latent Space of GANs.** With the rapid evolution of GANs, many works have tried to understand and control their latent space. Several methods apply GAN Inversion, where the latent vector that most accurately reconstructs a given image is sought. These methods either directly optimize the latent vector to minimize reconstruction error for every image [12, 37, 1], train an encoder to map images to the latent space [42, 47], or use a hybrid approach combining both [65, 64, 48]. Other methods learn to traverse the latent space in a semantically meaningful manner. A popular approach is to find linear directions that correspond to changes in a given binary labeled attribute, such as young ↔ old, or no-smile ↔ smile [15, 51, 20]. Jahanian et al. [29] find latent space paths that correspond to a specific image transformation, such as zoom or rotation, in a self-supervised manner. Härkönen et al. [23] find useful paths in a completely unsupervised manner. These paths are set to be the principal component axes (PCA) on an intermediate activation space – $W$ in the case of StyleGAN. Similar to the other methods, the computed transitions control one-dimensional attributes such as age or gender, as well as image transformations like zoom or rotation. Our method infers a latent representation for combining the attributes of two input images, thus performing, in a sense, learning-based GAN inversion. However, our method is able to separately edit identity and other facial attributes, which are more complex and multi-dimensional. This is in contrast to all aforementioned methods that control one-dimensional attributes only.

**Controlling Facial Attributes.** There is an abundance of works on face manipulation with various means of controlling the facial attributes. These can be categorized by whether they preserve identity manipulate other attributes or vice versa.

As for the former, some works are based on conditional GANs that translates between different domains such as young → old, or happy → angry [10, 11, 47, 38, 49]. These methods are limited to a discrete number of domains and require datasets with their associated labels, but work on unseen image. By comparison, face reenactment methods transfer expression and head pose (sometimes also illumination and eye gaze) from a source video to a target identity [32, 56, 57, 4]. But, there methods usually require training a network for each given identity, and assumes the availability of videos of it. Another line of identity-preserving works [52, 39, 58] train GAN-based Image-to-Image translation networks that preserve the identity of the input image, while a subset of other attributes are controlled by a different image. Unlike our method, these methods are all class-based, i.e. relying on having an identity-labeled image dataset with multiple images for each identity.

Face de-identification methods are of the latter category, editing the identity of a target image, while preserving other attributes, like expression, pose, illumination, etc. Sun et al. remove the face from the target image and complete it using a GAN [54], while other methods [19, 61] shift the identity using a pre-trained face recognition network, while keeping the general image relatively similar to the source. A popular approach is performing face swap [46, 50, 13, 5], in which the face in the target image is replaced by the one from the source image. Unlike previously mentioned methods, face swap allows controlling the generated identity which is copied from the source image. However, face swapping methods are generally limited to using a target face relatively similar to the source face. Our method, allows the editing of both identity and facial attributes, while also controlling the generated identity according to an input image. In contrast to other methods, our method is successful even when the input images are completely different, demonstrating our disentanglement capability. Furthermore, all aforementioned methods only alter the internal features of the face, usually by cropping a tight face region or by using a segmentation mask of the face, leaving the head and hair intact. This approach conflicts with the fact that numerous works have identified that the appearance of the head as a whole, and specifically the hair, are crucial for identification [53, 59, 3]. Our method, on the other hand, generates an entire human head, including the hair, thus better controlling and preserving the generated identity.
Figure 3: Our disentanglement scheme, as utilized in the facial identity application. Data flow is marked by solid lines, and the losses by dashed lines.

3 Method

Our method takes two images as input: $I_{id}, I_{attr}$. The goal is to generate an image with the identity from $I_{id}$ and all other attributes, specifically pose, expression and illumination from $I_{attr}$. The disentanglement task is therefore to disentangle identity from all other attributes. Once achieved, we can extract the identity from $I_{id}$ and the attributes from $I_{attr}$, and reassemble them into a combined representation of a new human head. This representation is then fed to the generator, to generate an image that respects both the identity of $I_{id}$ and attributes of $I_{attr}$. Encouraging this disentanglement, while generating state-of-the-art quality images, is notoriously difficult. The key idea of our work is to separate the two objectives, by learning to map the combined representation into the latent space of a pre-trained generator, and its existing semantics. For this reason, we use a pre-trained generator with semantics-rich, and expressive latent space.

As depicted in Figure 3, the network consists of two encoders $E_{id}$ and $E_{attr}$, a mapping network $M$, and a generator network $G$. The task of generating an image with the same identity as in $I_{id}$, and the attributes portrayed in $I_{attr}$, consists of two parts: extracting identity and attributes from the corresponding input images, and then reassembling them to create a new head representation and generating an image accordingly. For the former, we use the two encoders $E_{id}, E_{attr}$. For the latter, we combine the codes by concatenation:

$$z = [E_{id}(I_{id}), E_{attr}(I_{attr})]$$ (1)

and map $z$ into the latent space of a pre-trained state-of-the-art generator using $M$, and employ $G$ to generate the output image, $I_{out}$.

We use state-of-the-art StyleGAN as the pre-trained generator for all our experiments. Differently from other GANs, StyleGAN has two latent spaces: $Z$, which is induced by a fixed distribution, and $W$ induced by a learned mapping from $Z$. We choose to map the combined face code into $W$, as it is a more disentangled latent space than $Z$, thus more suitable to facilitate and accommodate image editing [31, 51]. The design choice of using an existing latent space, is crucial for a few reasons. Usually disentanglement is performed with the premise that given enough samples with constant factors, while other factors are varying, one could learn to identify the constant factors and disentangle it from the others e.g., LORD [18]. In our setting, the dataset does not contain more than one image of the same person. Therefore, it is unclear how could the network learn to disentangle. Our approach resolves this problem by leveraging a latent space that already exhibits some degree of disentanglement, achieved in a completely unsupervised manner. Moreover, by using a state-of-the-art generator, we alleviate the difficulty of learning to generate high-quality and high-fidelity images. However, training the mapping between the latent space of the encoder and $W$, is not trivial. Thus, we add a discriminator $D_W$ to help $M$ predict features that lie within $W$. $D_W$ is trained in an adversarial manner to discriminate between real samples from StyleGAN’s $W$ space and $M$’s predictions. Note that, thanks to our use of a pre-trained generator, there is no discriminator employed on $I_{out}$. Thus, side-stepping much of the difficulty of training adversarial methods.
3.1 Network Architecture

The $E_{id}$ encoder is a pre-trained ResNet-50 [25] face recognition model, trained on VGGFace2 [8], with loose crops including the hair. The $E_{attr}$ encoder is implemented as InceptionV3 [55]. For both encoders, their output is taken from the last feature vector before the FC classifier. The mapping network, $M$, is a fully connected network that consists of four fully connected layers with LReLU [24] activation layers. The generator, $G$ is a pre-trained StyleGAN synthesis network, trained on FFHQ [31]. $G$ takes our predicted $w$ vector as input and employs it normally through the AdaIN [28] layers. Both $E_{id}$ and $G$ are kept frozen during training, while all other networks are trainable.

3.2 Training and Losses

We create a dataset using StyleGAN in the following manner. We sample 70,000 random Gaussian vectors and forward them through a pre-trained StyleGAN. In the forward process, the Gaussian noise is mapped into a latent vector $w$, from which an image is generated, and we record both the image and the $w$ vector. The StyleGAN generated images are used as our training dataset, and the latent $w$ vectors are used as "real" samples for training $D_W$.

StyleGAN cannot create the entire human head space, specifically all human identities, from its latent space $W$. Some works [64, 1] used an artificially enlarged latent space, from which the generator may also create non-human images, including cats and bedrooms. We therefore choose to use a StyleGAN generated dataset to prevent the conflict between identity preserving and mapping into StyleGAN’s rich latent space $W$.

For adversarial loss, we use the non-saturating loss [21] with $R_1$ regularization [44]:

$$L_{adv}^D = - \mathbb{E}_{w \sim W} [\log D_W(w)] - \mathbb{E}_{z} [\log(1 - D_W(M(z)))] + \frac{\gamma}{2} \mathbb{E}_{w \sim W} \left[ \| \nabla_w D_W(w) \|_2^2 \right]$$ (2)

$$L_{adv}^G = - \mathbb{E}[\log D_W(M(z))]$$ (3)

An $L_1$ cycle consistency loss between $I_{id}$ and $I_{out}$ is used to enforce identity preservation:

$$L_{id} = \| E_{id}(I_{id}) - E_{id}(I_{out}) \|_1$$ (4)

As discussed, human perception is highly sensitive to minor artifacts in facial appearance, this is especially true when generating sequences of frames, where not only does every individual frame must look realistic, but the motion across frames must also be realistic. Facial landmarks model the possible motion of the human face, Therefore, we incorporate a sparse $L_2$ cycle consistency landmarks loss. Landmarks are extracted using a pre-trained network noted as $E_{lnd}$:

$$L_{lnd} = \| E_{lnd}(I_{attr}) - E_{lnd}(I_{out}) \|_2$$ (5)

Additional loss is exercised to encourage pixel-level reconstruction of $I_{attr}$. This loss is clearly motivated by our desire for the $I_{out}$ to be generally similar to $I_{attr}$. Intuitively, if $I_{id}, I_{attr}$ are the same image, we would expect our method to reconstruct this image. Furthermore, we would like to capture and preserve pixel-level information such as colors and illumination, not modeled by any other loss. For this end, we adopt the "mix" loss suggested in Zhao et al. [63], and use a weighted sum of $L_1$ loss and MS-SSIM loss:

$$L_{mix} = \alpha (1 - \text{MS-SSIM}(I_{attr}, I_{out})) + (1 - \alpha) \| I_{attr} - I_{out} \|_1$$ (6)

However, a pixel reconstruction might also affect the identity of $I_{out}$ by reconstructing facial features from $I_{attr}$. In order to prevent this, we employ the reconstruction loss only when $I_{id} = I_{attr}$, i.e. :

$$L_{rec} = \begin{cases} L_{mix}, & I_{id} = I_{attr} \\ 0, & \text{Otherwise} \end{cases}$$ (7)

6
The overall generator loss is a weighted sum of the above losses:

\[ L^G = \lambda_1 L_{adv}^G + \lambda_2 L_{id} + \lambda_3 L_{ind} + \lambda_4 L_{rec} \] (8)

Our training procedure is simple. We uniformly randomly sample images and latent vectors from our generated dataset. The images are used for \( I_{id}, I_{attr} \) and the latent vectors are used as "real" samples for \( D_{w} \). When \( I_{id} \neq I_{attr} \), the network learns to disentangle identity from attributes. Whereas when \( I_{id} = I_{attr} \) it learns to encode all the information needed for proper reconstruction.

### 3.3 Implementation Details

We use StyleGAN pre-trained at 256x256 resolution in all our experiments. We take \( I_{id} \neq I_{attr} \) every third iteration, and \( I_{id} = I_{attr} \) otherwise. \( E_{ind} \) is implemented using a pre-trained landmarks regression network [17], trained to regress 68 facial keypoints. Training is performed using the Adam [35] optimizer, with \( \beta_1 = 0.9, \beta_2 = 0.999 \). We follow Heusel et al. [26] and use learning rates of \( 1 \times 10^{-5} \) for \( G \)’s loss and \( 4 \times 10^{-5} \) for \( D_{w} \)’s loss. Loss weights are set to \( \lambda_1 = 1, \lambda_2 = 1, \lambda_3 = 0.001, \lambda_4 = 0.02, \alpha = 0.84 \) and \( \gamma = 10 \). The network is trained end-to-end with batch size 6 on a single NVIDIA Titan XP GPU and requires roughly a day to converge.

### 4 Experiments

We perform extensive experimentation to evaluate our method, mainly through two aspects: the quality of the disentanglement, or how well we control the identity without affecting other facial attributes, and the quality of the synthesized images. We compare our method to state-of-the-art methods both qualitatively and quantitatively.

First, a qualitative inspection of the results can be seen in Figure 4. The array of images illustrates the degree of identity preservation of our method (along the columns) and preservation of the rest of the attributes (along the rows). In addition, our method successfully preserves the overall head shape and the hair – a pivotal yet elusive part of true identity preservation. Additionally, we observe consistency in details such as the existence and appearance of glasses. This is a crucial element when considering consistency, and is especially relevant when, for example, generating consecutive frames for a sequence. Note that this disentanglement and preservation capabilities cannot be achieved by the style mixing approach proposed in the original StyleGAN paper, where styles entangle identity and other semantic attributes.

As previously mentioned, our method inherits the properties of the chosen generator \( G \) and its latent space. For the running example of this paper, this generator is StyleGAN. Shen et al. [51] have demonstrated that StyleGAN’s latent space \( \mathcal{W} \) is well behaved, permitting the smooth editing features by interpolation of the latent code. However, this and other previous art [64] have demonstrated this property for one-dimensional properties, such as age or the extent of a smile. In contrast, our proposed mapping identifies latent codes which represent more involved differences, namely the much discussed high-dimensional identity property, or a combination of expression, pose, and lighting. In Figs. 5 and 6 we demonstrate the smooth editing of these elaborate features by interpolation of the latent codes, thus showing that the StyleGAN’s latent space \( \mathcal{W} \) is well behaved even with respect to such features, and that we indeed inherit these advantages.

In each figure, the interpolated feature is extracted from the images on the far ends, while the constant feature is extracted from a third image, not shown. Using these as inputs, we then infer two \( \mathcal{W} \) vectors and interpolate between them. The images generated by the interpolated values appear in the middle of each of these figures, and portray a pleasant and natural transition between the various explored properties. In Figure 5, we demonstrate that we accurately and consistently preserve the identity while smoothly interpolating expression, pose and illumination, which are also accurately preserved from their respective inputs. Specifically, note the successful interpolation of illumination presented on the bottom line of the figure. In Figure 6 we demonstrate that we accurately and consistently preserve the attributes while smoothly interpolating the identity. Note that all images generated during interpolation are of high visual quality and realism.

We further qualitatively compare our results against those of LORD [13] on images from CelebA [40] in Figure 7. Note that, LORD was trained on CelebA, whereas our method was trained on a fundamentally different dataset, making this comparison incredibly challenging for our method.
Figure 4: Feature combination results. For every image in the table, identity is taken from the top, and the rest of the attributes (including expressions, orientation, lighting conditions, etc.) from the left. All images (both inputs and output) were generated using StyleGAN.

Nevertheless, our method achieves superior results. LORD uses low resolution, 64x64 tight face crops, while our method handles higher resolution, of 256x256 loose crops. For a fair comparison, each method uses its own cropped input configuration, and we crop and resize the output images to make them visually comparable. The red frames indicate the region of the image that is input to LORD. As previously discussed, we inherit the performance of the employed pre-trained generator and its latent space. As it was shown [1,64] StyleGAN in unable to generate the entire human head space from $W$. This is most evident for the head pose, where StyleGAN generates faces with no roll angle, because their training data is aligned to remove it. Similarly, not all human identities can be generated. By inheriting StyleGAN’s performance, our method generates the closest possible identity, which qualitatively and quantitatively is very similar (see Table 1).

As can be observed, our method better preserves the facial expression of the attributes image, regardless of the expression of the identity image, indicating a strong disentanglement between identity and expression. This is most noticeable when observing the mouth, where our method is able to generate various mouth shapes. On the other hand, LORD struggles in preserving expression when the identity image has a non-neutral expression, and preserving the challenging open-mouth expression. Furthermore, our results have a much higher visual quality than LORD’s, which are
Figure 5: Disentangled interpolation of attributes while preserving identity. In each line, attributes are extracted from two images (both ends of the spectrum), and the identity is extracted from a third image (not shown). For each of these we infer a $w$ vector, and interpolate between the resulting two (middle).

Figure 6: Disentangled interpolation of identity while preserving the other attributes. The setting is identical to the one in Figure 5, only here the attributes are extracted from the same image (not shown), and the identity is extracted from two images (both ends of the spectrum), and is interpolated in the space of $\mathcal{W}$ (middle).

| Method   | FID ↓ | Identity ↑ | Expression ↓ | Pose ↓ |
|----------|-------|------------|--------------|--------|
| LORD [18] | 181.36 | 0.20 ± 0.11 | 20.74 ± 5.83 | 13.34 ± 15.00 |
| Ours     | 49.81  | 0.60 ± 0.09 | 5.35 ± 4.61  | 9.74 ± 13.16  |

Table 1: Quantitative Comparison of our method with LORD

of low resolution and contain artifacts, most noticeable is the checkerboard effect, which should not be attributed to the resizing of the image as it also exists in the original resolution. We further quantify the aforementioned differences in performance by conducting a quantitative evaluation. We evaluate the methods’ ability to disentangle and preserve underlying factors composing the human head from different sources, as well as evaluating image quality. The evaluation is performed by randomly sampling $5K$ pairs of images from FFHQ, to be used as identity and attribute inputs. We then run both methods to infer face images and calculate four factors: image quality and identity, pose and expression preservation. The results are displayed in Table 1. In order to test identity preservation, we employ state-of-the-art face recognition network, namely ArcFace [14], and adopt the cosine similarity metric to compare the identity of $I_{id}$ and $I_{out}$. Note that ArcFace, is completely different than the face recognition network used during training, both in the training set and loss. The accuracy of expression preservation is calculated as Euclidean distance between $2D$ landmarks of $I_{attr}$ and $I_{out}$, inferred using dlib [34]. Similarly, pose preservation is calculated as Euclidean
Figure 7: Qualitative Comparison of our method (odd rows) to LORD [18] (even rows) on samples from CelebA. Our results have a much better visual quality and preservation of identity and facial attributes (see Table [1]).
distance between Euler angles of $I_{\text{attr}}$ and $I_{\text{out}}$. For each of the above we calculate the mean and standard deviation across the test set. Last, we evaluate image quality using FID [26] on 10K output images of both methods. As can be seen in Table 1, our approach is superior to LORD in all four metrics.

We also compare our results with latest face swapping method FaceShifter [36]. As discussed earlier, face swapping is a different yet related task that focuses on replacing inner face features only. We qualitatively demonstrate the differences in our application from face swapping in Figure 8. Our method preserves the inner face features from the identity image, with similar quality to FaceShifter. However, we also preserve the head shape and hair from the identity image, regardless of that from the attributes image, overall preserving the identity better. Furthermore, FaceShifter is limited to operate on relatively similar images, as face swapping method usually are. When input images are different, noticeable artifacts like phantom hair (rows 1,2) and two jaw lines (row 2) may appear. Even when no artifacts are created, the output may be not recognized as either of the input identities and often create an unrealistic face simply because it depicts a very unusual appearance (row 3).

![Figure 8: Qualitative comparison to FaceShifter [36] on samples from FFHQ [31]. As can be seen, our method better preserves the identity as it does not only preserve inner facial features, but the entire head and hair, features which are known to be crucial for identity recognition by humans. It can also be observed that face swapping methods struggle with faces with significantly different appearances.](image)

Finally, motivated by our ability to disentangle identity from attributes and preserve both from different sources, we examine the coherency of the generated identity through the generation of sequences. To generate the sequence, we use a single, unseen image to define the target identity, and a sequence of a facial performance to define the rest of the attributes. Generating such a sequence can be practical both for the case where the de-identification of the person in the driving input sequence is desired, or when one would like to reenact a single, unseen, given image. For the case of de-identification, our method is unique because it completely hides the original identity, both from state-of-the-art face recognition networks and from human eyes. This is in contrast to previous
Figure 9: Talking head sequence. The first row consists of consecutive frames from a driving attributes sequence, while the rest of the rows are frames generated by our method. We demonstrate smooth control over facial expression and pose while maintaining constant identity.

Figure 10: Cropped mouth regions from Figure 9. Our method is able to preserve subtle lips movement, critical for talking head sequence realism.

methods [19], that perform minimal facial modification to fool face recognition methods. In this case, if the input and output images were put side by side, they would still be recognized as the same person by a human. Our method generates a different person, having a completely different appearance. A sample of our results is displayed in Figure 9 and in the accompanying video. Consecutive frames from the driving sequence are displayed in the first row, and the rest of the rows are our results. Note the different overall appearance of our results compared to the driving sequence. For example, the bottom three rows are generations of different women, all with long hair, while the input is a man with a beard and no hair. This simple approach achieves smooth temporal control over pose and expression, and a very stable and coherent identity for the entire sequence. To better observe details, we crop the mouth region from these frames and display them in Figure 10. Note the subtle changes in mouth shapes along the sequence.

5 Discussion and Conclusions

This paper presented a novel disentanglement method, applied to the highly challenging domain of human heads. The key idea of mapping the disentangled representation to the latent space of a pre-trained GAN is both novel and crucial. It enables state-of-the-art quality synthesis, while requiring modest supervision. Through extensive experimentation, we have further demonstrated the effectiveness and versatility of the method.

We have proposed a novel concept of disentanglement, achieved by mapping to the semantically rich latent space of a pre-trained GAN. This concept is generic and could be applied to any data domain and GAN architecture, assuming its latent space is well behaved. Thus, our work is orthogonal to ongoing research on unconditional image generation, from which the proposed framework can only gain. Furthermore, this concept allows concentrating on the preservation of image properties, instead of explicitly reducing “leakage” of information between the two parts of the disentangled
representation $Z$. This is true because the mapping process, which translates between $Z$ and the latent space of the generator $W$, takes only the relevant information from each of the parts, and disregards any impurities in the separation of the representation, as has been clearly demonstrated by the experiments.

As many works [51,29,64,23] have shown, the latent space of GANs is well-behaved and allows great controlled editing opportunities. All of them, however, have found generic linear directions, along which linear properties can be enhanced or reduced, in a disentangled fashion. Identity, on the other hand, is a complex and high-dimensional factor that cannot be edited by one-dimensional value changes. By exhibiting control over the identity, our method continues the direction of demonstrating the incredible strength and possibilities hidden in the latent space of GANs, and StyleGAN in particular.

Our approach further relies on the existence of a network, or any other derivable method, to classify, or evaluate, the feature of interest $f$. In the case of human faces, we have also leaned on a similar network to help with identifying facial landmark positions. This was needed due to the extremely sensitive human perception of faces. Other than these networks, our dataset does not contain any labeling, nor several images of the same identity. This setting poses a rather weak form of supervision, especially when compared to the common setting of class-supervised disentanglement. The supervision in our method is manifested solely through the used pre-trained networks. These, however, can be trained on fundamentally different datasets and tasks, so they do not impose an inhibiting requirement.

As discussed, we inherit the generative capabilities of the used pre-trained generator. Of course, alongside these, we also inherit any limitations the generator might have, including those imposed by its training dataset. For example, the preprocessing method used by StyleGAN aligns heads such that there is no roll angle, and renders yaw rotations to be highly correlated with translation. Thus, StyleGAN-based generations, including ours, inherit these properties. Furthermore, it was recently shown that StyleGAN does not cover the entire manifold of human faces and heads, forcing many approaches [1,64,48] to work with an artificially enlarged latent space, named $W^+$. Introducing manipulations on $W^+$ to our methods may significantly increase the expressiveness of our model, but may come at the cost of both generation and disentanglement qualities. We leave this investigation as an exciting avenue for future work. Regardless, this work introduces a powerful concept, where generative networks are employed as "backbones" for disentanglement tasks, which can most probably be explored much further in future research.
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