3D-aware Facial Landmark Detection via Multiview Consistent Training on Synthetic Data

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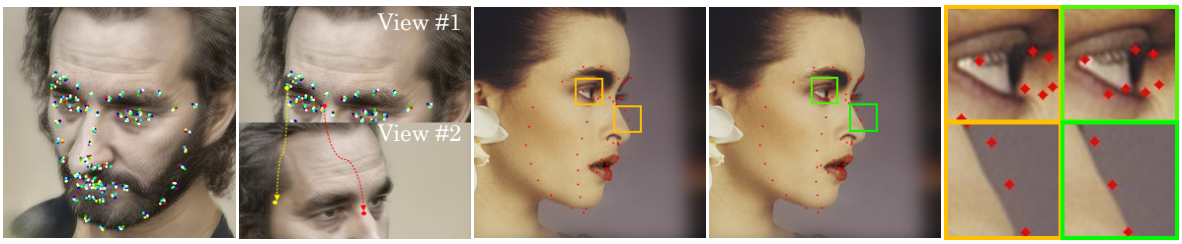

(a) Annotation Inconsistency | (b) Multi-view Inconsistency | (c) Result of DAD-3DNet | (d) Result of DAD-3DNet+ (Ours) | (e) Closeout View of (c) and (d)

Figure 1. We plot the landmark annotations labeled by different annotators with different colors in (a). We project two annotated 3D points from View #1 to View #2, and we can find that the points are inaccurate if we look at the projected points in view #2. We show the landmark detection improvement in (c) (d), and (e). After refined by the proposed 3D-aware learning, the detected facial landmark is better aligned with the identity.

Abstract

Accurate facial landmark detection on wild images plays essential role for human-computer interaction, entertainment, and medical applications. Existing approaches are limited by the in-the-wild data and fail to enforce 3D consistency when detecting 3D/2D facial landmarks. On the other hand, with recent advances in generative visual models and neural rendering, we have witnessed rapid progress towards high quality 3D image synthesis. In this work, by leveraging synthetic data, we propose a novel multi-view consistent learning strategy to improve 3D facial landmark detection accuracy on in-the-wild images. The proposed 3D-aware module can be plugged into any learning-based landmark detection algorithm. We demonstrate the superiority of the proposed plug-in module with extensive comparison against state-of-the-art methods on several real and synthetic datasets.

1. Introduction

Accurate and precise facial landmark detection plays a significant role in computer vision and computer graphics applications, such as face morphing [53], facial reenactment [57], 3D face reconstruction [17, 18, 30], head pose estimation [38], face recognition [1, 10, 13, 19, 32, 41, 69], face generation [11, 21, 59, 67], to name a few. In these applications, facial landmark detection provides great sparse representation to ease the burden of network convergence in different training stages. For instance, as a facial prior, it provides good initialization for subsequent training [65–67, 74], good intermediate representation to bridge the gap between different modalities for content generation [11, 27, 50, 77], loss terms which regularize the facial expression [11, 51], or evaluation metrics to quantitatively evaluate the facial motion quality [52, 71, 76].

The aforementioned applications require that facial landmark detection to be accurate even with significantly varied facial appearance under different identities, facial expressions, and extreme head poses. Tremendous efforts have been devoted to boost the performance [15, 22–24, 29, 34, 40, 55, 62, 72, 73, 75, 80, 82], which often rely on manually annotated large-scale lab-controlled or in-the-wild image datasets [4, 34], in order to handle arbitrary facial expressions, head poses, illumination, facial occlusions, etc.

However, even with high cost of human labeling, *consis-*

tent and *accurate* manual annotation of landmarks remains challenging [22,23,34]. It is very difficult, if not impossible, to force a person to annotate the facial landmark keypoints at the same pixel locations for faces of different poses, let along different annotators under different labeling environments. Such inconsistent annotations in training images are often the killing factor to learn an accurate landmark localization model. For example, Fig. 1(a) shows the inconsistency of human annotations, which limits the training convergence of previous methods. In Fig. 1(b), we project the landmarks detected by a state-of-the-art algorithm [34] from view #1 to view #2. We can observe obvious 3D inconsistencies, which lead to poor landmark detection accuracy on facial images with extreme head pose.

To mitigate this annotation inconsistency issue, we propose to learn facial landmark detection by enforcing multi-view consistency during training. Given the images of the same facial identity captured with different head poses, instead of detecting facial landmark at each separate facial image, we propose a multi-view consistency supervision to locate facial landmark in a holistic 3D-aware manner. To enforce multi-view consistency, we introduce self-projection consistency loss and multiview landmark loss in training. We also propose an annotation generation procedure to exploit the merits of lab-controlled data (*e.g.*, multi-view images, consistent annotations) and in-the-wild data (*e.g.*, wide range of facial expressions, identities). Thanks to the synthetic data, our method does not rely on human annotation to obtain the accurate facial landmark locations. Therefore, it alleviates the notorious impact of learning from inaccurate and inconsistent annotations.

We formulate our solution as a plug-in 3D aware module, which can be incorporated into any facial landmark detector and can boost a pre-trained model with higher accuracy and multi-view consistency. Extensive experiments demonstrate the effectiveness. The main contributions of our work are as follows:

- To the best of our knowledge, for the first time, we show that our synthetic dataset combines the merits of lab captured face image data (*e.g.* multi-view) and the in-the-wild face image datasets (*e.g.* appearance diversity). Compared with the traditional graphics pipeline, the face images generated by our scheme is more realistic, leading to better domain adaptability in the trained models. Compared with the generative models, the data generated by our scheme is more controllable and multi-view consistent.

- We propose a novel 3D-aware optimization module, which can be plugged into any learning-based facial landmark detection methods. The proposed module is able to improve the detection accuracy on unseen images beyond the training data by simply refining the baseline models with our synthesized data.

- We demonstrate the performance improvements of our module built on top multiple baseline methods on simulated dataset, lab-captured datasets, and in-the-wild datasets.

- We collect a simulated multi-view face dataset, DAD-3DHeads-Syn, without domain gap, and will release it to facilitate future research.

2. Related Work

In this section, we review face landmark datasets and detection algorithms that are most related to our approach. We also provide a brief review of data simulation tools related to our work.

2.1. Face Landmark Detection Dataset

Lab-controlled dataset. Datasets under "controlled" conditions [8, 20, 36, 39, 46, 47, 63, 64, 70] typically collect video/images from indoor scenarios with certain restrictions, *e.g.* pre-defined expressions, head poses, etc. For example, FaceScape dataset [64] contains 938 individuals and each with 20 expressions using a 68-camera array under controlled illumination and positions. Thus, it contains aligned and consistent multi-view images and facial landmark annotations. However, the identities, poses, and expressions are limited. In addition, the environment conditions are fully controlled. These result in limited generalization capability of models trained on this dataset. Moreover, the annotation workflow of such dataset is expensive and hard to scale.

In-the-wild dataset. The boom of internet image sharing enabled many "in-the-wild" facial landmark datasets [3, 7, 32, 48, 83] that are collected from the webs to facilitate facial landmark detection research. However, manually annotating facial landmarks on in-the-wild images is a time-consuming process and not scalable. Zhu et al. [81] released 300W-LP by extending the original 300W dataset with synthetic images with extreme pose through image profiling of frontal pose images. However, the novel view images are generated by simply applying rotation matrix on the original images, which leads to limited view range and poor image quality. Meanwhile, 300W-LP lacks diversity in face appearance and expression because of the intrinsic limitations of 300W. Recently, Martyniuk *et al.* [34] introduce a new dataset, DAD-3DHeads by proposing a novel annotation scheme, in which a annotator can see the texture rendered onto the 3D mesh with respect to their fitting to verify that the facial landmark annotation results are accurate. The proposed scheme addresses the problems exhibited by existing labeling tools, such as "guessing" the positions of the correct landmarks for invisible parts of the head, thus

enabling accurate annotations. DAD-3DHeads dataset contains 44,898 in-the-wild images, covering extreme facial expressions, poses, and challenging illuminations. However, even with the help from the proposed annotation scheme, the DAD-3DHeads still has some drawbacks. First, annotations across different annotators are inconsistent (see Fig. 1) and those noisy annotations could affect the training of the detection network. Second, since the depth is estimated by FLAME [33], annotation accuracy is limited by the FLAME model. Third, it lacks of multi-view images such that the 3D consistency of landmark detection methods cannot be investigated.

2.2. Data Simulation

Simulation [26, 28, 35, 42, 44, 45, 49, 58, 60, 61, 68] is a useful tool in situations where training data for learning-based methods is expensive to annotate or even hard to acquire. For example, Zeng *et al*. [68]] and Richardson *et al*. [42] used 3D Morphable Model (3DMM) to render training data with different lighting condition, identity, expression, and texture basis elements for reconstructing detailed facial geometry. However, the simulated images by these approaches lack of realism have severe domain gap compared with real world captures, limiting the usage. Bak *et al*. [2] adapt synthetic data using a CycleGAN [79] with a regularization term for preserving identities. Ayush *et al*. [56] use the images and latent code generated by StyleGAN [79] to train a controllable portrait image generation model. However, it is hard to control the attribute consistencies of images simulated by generative models, which limits the usage of the generated datasets.

2.3. Face Landmark Detection Algorithms

Traditional facial landmark detection methods leverage either holistic facial appearance information [12], or the global facial shape patterns [31, 83]. They yield reasonable results for images captured in lab-controlled environments with frontal faces and good lighting, however the performance on most of in-the-wild images is inferior.

Recently, deep learning-based algorithms have made promising progress on 2D facial landmark localization [15, 22–24, 29, 34, 40, 55, 62, 72, 73, 75, 80, 82] in terms of robustness, generalizability, and accuracy. FAN [6] constructs, for the first time, a very strong baseline by combining a state-of-the-art architecture for landmark localization and train it on a very large yet synthetically expanded 2D facial landmark dataset. To address self-occlusion and large appearance variation, Zhu *et al*. [80] propose a Cascaded Convolutional Neural Network and Optimized Weighted Parameter Distance Cost Loss function to formulate the priority of 3DMM parameters during training instead of predicting facial landmark keypoints. To further address the problems of shape reconstruction and pose estimation simultaneously, Martyniuk *et al*. propose an end-to-end trained DAD-3DNet [34] to regress 3DMM parameters and recovering the 3D head geometry with differential FLAME decoder. However, due to the intrinsic limitation of the manually annotated in-the-wild dataset, the detection results are affected by the annotation noise and the 3D inconsistency of the single view images. In this paper, we mainly focus on improving the performance of deep-learning based methods.

Dataset Type	Lab-Controlled	In-the-wild	Ours
Examples			
In-the-wild	✗	✓	✓
Large Scale	✗	✓	✓
Balanced	✓	✗	✓
Multiview Consistent	✓	✗	✓
Annotation Consistent	✓	✗	✓
Scalable	✗	✗	✓

Figure 2. The feature comparison of different type of datasets.

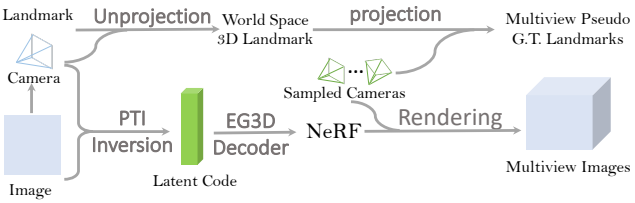

Figure 3. The proposed data simulation pipeline.

3. Balanced and Realistic Multi-view Faces Synthetic Dataset

Existing datasets are either lab-controlled captures [63, 64], or in-the-wild collected but lack of balanced multi-views [34, 81]. Moreover, we believe there are four desired properties that a good facial landmark dataset should fulfill: (1) containing full range of multi-view images; (2) can bridging the domain gap between the dataset and the real-world captured images; (3) containing diverse facial appearance including different poses, expressions, illuminations, and identities; (4) consistent and accurate annotations across the whole dataset (5) easy to obtain and scalable. Our dataset meets all the properties (Fig.2).

Unlike previous graphics or generative model-based data synthesis approaches described in Sec. 1, we propose a novel facial dataset simulation scheme by leveraging Neural Radiance Field (NeRF) [37] to facilitate facial landmark detection tasks. Fig. 3 shows our dataset creation pipeline.

Specifically, we choose DAD-3DHeads [34] as our initial dataset since it contains images under a variety of extreme poses, facial expressions, challenging illuminations, and severe occlusions cases. As for the image generation, inspired by GAN inversion [78], we first fit a latent code to each image in DAD-3DHeads datasets using EG3D [9] as decoder by following Pivotal Tuning Inversion (PTI) [43]. Then we can use EG3D to decode it to NeRF. Next, we use volume rendering on the NeRF with 512 uniformly sampled camera views from a large view range, producing 512 multi-view images. For landmark annotation, we start with the well-annotated groundtruth 3D landmarks of the original images from the DAD-3DHeads dataset. We first use Deep3DFace [14] to estimate the camera extrinsics with fixed camera intrinsics. Then we use the estimated camera view to unproject the annotated landmarks to 3D space. At last, we project the 3D landmarks to the 512 sampled camera views to obtain landmark annotation on the simulated views. The simulated dataset not only inherits the merits of DAD-3DHeads (*e.g.* diverse identities, expressions, poses, and illuminations), but also comes with a lot of new features (*e.g.*, balanced head pose, consistent annotation, and multi-view images). In total, there are 2,150,400 training pairs and 204,800 testing pairs in our extended dataset.

4. 3D-Aware Multi-view Consistency Training

4.1. Overview

The state-of-the art landmark detectors [5,34] can output reasonable results on in-the-wild images. However, we may observe that the predicted landmark are floating on the face surface instead of fitting the face perfectly in a lot of cases. We can easily verify if the detected landmark fits the face by projecting the detected landmark to another view (see Fig. 1(b)). Innovated by this phenomenon, we propose a novel 3D-Aware training module $\mathcal{R}$ to further improve the performance of baseline detection algorithm F.

Given a facial landmark detection network $F_\theta(\cdot)$ pretrained on dataset $\mathcal{D}$, the proposed module $\mathcal{R}$ further refine the network parameters θ by leveraging our simulated DAD-3DHead-Synth dataset $\hat{\mathcal{D}}$ and $\mathcal{D}$. Our module $\mathcal{R}$ can be formulated as:

$$F_{\theta^*} \leftarrow \mathcal{R}(F_\theta, X, V_{1,\dots,N}), X \in \mathcal{D}, V_{1,\dots,N} \in \hat{\mathcal{D}}, \quad (1)$$

where X is the image batch sampled from $\mathcal{D}$ and $V_{1,\dots,N}$ are multi-view images sampled from $\hat{\mathcal{D}}$. Our goal is to refine the network parameters θ through exploring 3D information among multi-view images and applying a novel projection consistency during the fine-tuning process. Our module $\mathcal{R}$ does not result in any new network parameters and can be plugged into any learning-based network. We show the training protocol in Alg. 1.

Algorithm 1 3D-Aware Plug-in Module.

Input: pretrained detector F with weights θ, M single-view images $I_{1,\dots,M} \in \mathcal{D}$ along with ground truth landmark $\mathrm{L}_{1,\dots,M}$, paired N multi-view images $V_{1,\dots,N} \in \hat{\mathcal{D}}$ along with ground truth landmark $\mathrm{L}_{1,\dots,N}$.
Output: detector F with updated weights θ^*
Initialization: set θ to pre-trained weights by it's initial training,
Unfreeze θ
for number of iterations **do**
Output predicted landmarks $\hat{\mathrm{L}}_{1,\dots,N}$ for each view.
Randomly sample P landmarks from them, $(1 < P \leq N)$.
Cast the landmarks into world space and estimate the approximate 3D landmark $\dot{\mathrm{L}}$ using Eq. 2, 3, 4, 5
Project $\dot{\mathrm{L}}$ onto the image planes of remaining Q views $(Q = N - P)$ using Eq. 6, 7
Calculate Self-Projection Consistency Loss $\mathcal{L}_{\text{Self-Cons}}$ using Eq. 8.
Calculate Mesh Consistency Consistency Loss $\mathcal{L}_{\text{Mesh-Cons}}$ using Eq. 9
Calculate Multiview Landmark Loss $\mathcal{L}_{\text{Multiview}}$ using Eq. 10
Calculate Total Loss $\mathcal{L}$ using Eq. 11
$\theta^* \leftarrow Adam\{\mathcal{L}\}$

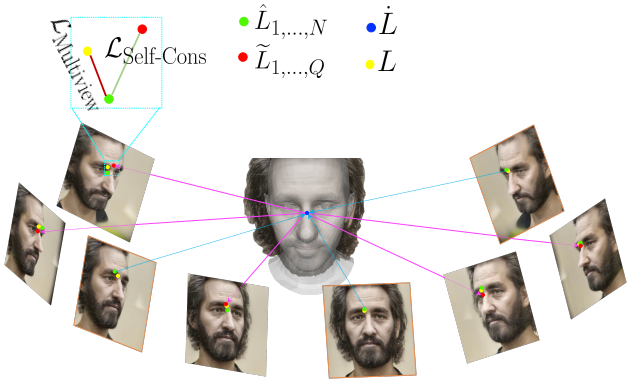

Figure 4. Multi-view Consistency Supervision. Predicted landmarks $\hat{\mathrm{L}}_{1,\dots,N}$, estimated the 3D landmark $\dot{\mathrm{L}}$, projection landmarks $\tilde{\mathrm{L}}_{1,\dots,Q}$, and ground truth landmarks L are denoted as green, blue, red, and yellow points respectively. The process calculating 3D landmark $\dot{\mathrm{L}}$ and the projection procedure are shown as light blue and pink arrow lines respectively. $\mathcal{L}_{\text{Self-Cons}}$ and $\mathcal{L}_{\text{Multiview}}$ are represented as red line segment and light green segment respectively.

4.2. Multi-view Consistency Supervision

We propose a novel multi-view supervision to enforce the baseline network learn to be 3D consistent. To simplify notation, we ignore the batch dimension and fixed camera intrinsic matrix. For every training iteration, we randomly

sample N image and landmark pairs $\{V, \mathrm{L}\}_{1,..,N}$ from $\hat{\mathcal{D}}$ and M image and landmark pairs $\{I, \mathrm{L}\}_{1,..,M}$ from initial dataset $\mathcal{D}$[1].

We pass $V_{1,..,N}$ to the baseline network F to obtain predicted landmarks $\hat{\mathrm{L}}_{1,..,N}$ which are notated as green points in Fig. 4, and randomly select P predicted landmarks $\hat{\mathrm{L}}_{1,..,P} \in \mathbb{R}^{P\times 68\times 2}$ from $\hat{\mathrm{L}}_{1,..,N}$ to calculate the "canonical" 3D landmark $\dot{\mathrm{L}} \in \mathbb{R}^{68\times 3}$ as shown by the blue point in Fig. 4 through Direct Linear Transformation (DLT) [16, 25] which is illustrated using blue arrowed lines in Fig. 4. Since all P views are simulated with pre-defined camera views using volume rendering (see Sec.3), the camera extrinsic matrix $\mathbb{M}_{1,..,P}$ are known. We calculate each keypoint of the "canonical" 3D landmark $\dot{\mathrm{L}}^{(k)} \in \mathbb{R}^3, 1 \le k \le 68$, as follows:

$$\mu_p = \mathbb{M}_p[0,:] - \mathbb{M}_p[2,:] \cdot \hat{\mathrm{L}}_p^k[0] \in \mathbb{R}^4, \tag{2}$$

$$\upsilon_p = \mathbb{M}_p[1,:] - \mathbb{M}_p[2,:] \cdot \hat{\mathrm{L}}_p^k[1] \in \mathbb{R}^4, \tag{3}$$

$$\mathbf{A} = [\mu_1 \mid \mu_2 \mid ... \mid \mu_p \mid \upsilon_1 \mid \upsilon_2 \mid ... \mid \upsilon_p]^T \in \mathbb{R}^{2P\times 4}, \tag{4}$$

$$\dot{\mathrm{L}}^{(k)} = \Big(\mathbf{A}[:,:3]^T \quad \mathbf{A}[:,:3]\Big)^{-1}\mathbf{A}[:,:3]^T(-\mathbf{A}[:,3]), \tag{5}$$

where, $p, 1 \le p \le P$ is the index of views. By Eq. 2 and Eq. 3, we first calculate the projection constraints for $\dot{\mathrm{L}}_{(k)}$, i.e., $\mu_p[:3] \cdot \dot{\mathrm{L}}^{(k)} + \mu_p[3] = 0$, where '$\cdot$' indicates the dot product. Then we can stack all of the constraints into $\mathbf{A} \in \mathbb{R}^{2P\times 4}$ by Eq. 4. At last, we compute $\dot{\mathrm{L}}^{(k)}$ with a least square approach (Eq. 5).

After obtaining the "canonical" 3D landmark $\dot{\mathrm{L}}$, we project it onto the image planes of rest of $Q = N - P$ views to obtain the projected landmark $\tilde{\mathrm{L}}_{1,..,Q}$, shown as red points in Fig. 4, by the following equations:

$$s = \mathbb{M}_q[:,:3]\dot{\mathrm{L}}^{(k)} + \mathbb{M}_q[:,3] \in \mathbb{R}^{3\times 1}, \tag{6}$$

$$\tilde{\mathrm{L}}_q^{(k)} = \begin{bmatrix} s[0]/s[2] \\ s[1]/s[2] \end{bmatrix} \in \mathbb{R}^{2\times 1}, \tag{7}$$

where, in our case, $1 \le q \le Q$.

Self-Projection Consistency Loss. Since all M views are sampled from one NeRF with different camera views, the predicted landmarks $\hat{\mathrm{L}}_{1,..,Q}$ and the projected landmarks $\tilde{\mathrm{L}}_{1,..,Q}$ should be consistent, illustrated using light blue segment connecting red point and green point. The loss can be formulated as

$$\mathcal{L}_{\text{Self-Cons}} = \sum_{q=1}^{Q} \parallel \hat{\mathrm{L}}_q - \tilde{\mathrm{L}}_q \parallel_1 . \tag{8}$$

[1] $\mathcal{D}$ is DAD-3DHeads dataset when training DAD-3DNet and is AFLW2000-3D when training 3DDFA.

Mesh Consistency Consistency Loss[2] Besides the self-projection consistency, all the N views also share one mesh topology in canonical space. Therefore, we apply a mesh consistency loss in canonical space calculated by:

$$\mathcal{L}_{\text{Mesh-Cons}} = \sum_{n=1}^{N} \parallel \hat{\mathrm{M}}_n - \dot{\mathrm{M}} \parallel_2, \tag{9}$$

where $\hat{\mathrm{M}}_n$ is the predicted mesh of view n in canonical space, and $\dot{\mathrm{M}}$ is the ground truth mesh of the original reference image.

Multiview Landmark Loss. We also minimize the distance between predicted 2D facial landmarks and the corresponding multi-view ground truth landmarks we obtained in Sec.3, which are denoted as yellow points in Fig. 4. The loss can be formulated in the following equation:

$$\mathcal{L}_{\text{Multiview}} = \sum_{q=1}^{N} \parallel \hat{\mathrm{L}}_q - \mathrm{L}_q \parallel_1 . \tag{10}$$

We also incorporate the original loss of the baseline method computed with image and landmark pairs $\{I, L\}_{1,..,M}$ from dataset $\mathcal{D}$ to stabilize our 3D-aware training. The overall loss is:

$$\mathcal{L} = \lambda_1\mathcal{L}_{\text{Self-Cons}} + \lambda_2\mathcal{L}_{\text{Mesh-Cons}} + \lambda_3\mathcal{L}_{\text{Multiview}} + \mathcal{L}_{\text{original}}, \tag{11}$$

where $\lambda_{1,2,3}$ are hyper parameters that weights the balance between each components. We set $\lambda_{1,2,3}$ to 0.1 empirically.

Note that our training is a plug-in module and can be incorporated into any existing facial landmark detector easily. For different pretrained models, we just need to change $\mathcal{L}_{\text{original}}$, while other novel loss components calculated on our balanced synthetic dataset $\mathcal{D}$ can be applied directly. we show this plug-in capability on top of different baseline methods (*e.g.*, DAD-3DNet [34] and 3DDFA [22]), and demonstrate that our 3D-aware training indeed improves their performance (see Sec. 5).

5. Experiments

5.1. Experimental Settings

Training Details. We implement our algorithm in Pytorch and adopt ADAM to optimize the baseline networks. We run our 3D-aware training for 100 epochs with a batch size of 4, and a learning rate of 1×10^{-4} on each baseline network.

Dataset. Besides DAD-3DHeads, we use another three datasets to conduct the evaluations.

- **DAD-3DHeads** [34] is the state-of-the-art in-the-wild 3D head dataset, which contains dense, accurate annotations, and diverse facial appearances. It consists of

[2] We can apply it depending on whether the baseline network outputs mesh. In our case, the 3DDFA [22] and DAD-3DNet [34] both do.

Figure 5. The visual results of Dlib [31], FAN [5], 3DDFA [22], our refined 3DDFA+, 3DDFA-V2, DAD-3DNet [34], and our refined DAD-3DNet on images randomly sampled from DAD-3DHeads [34] testing set. We show the enlarged error region (while box) in the middle row.

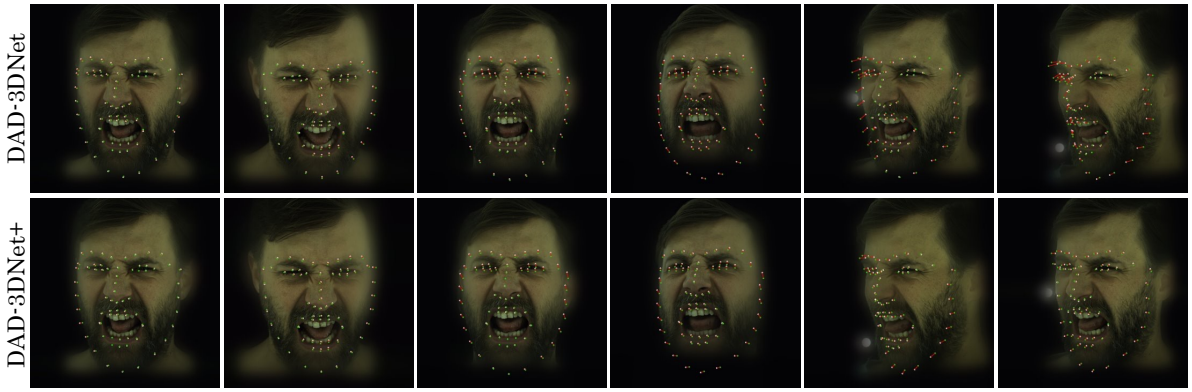

Figure 6. The error visualization of DAD-3DNet [34] and our DAD-3DNet+ on MultiFace [63] dataset. The white, green dots are the ground truth landmark and predicted landmark, respectively. We use the red line to show the error distance. From left to right, the head pose increases gradually.

Table 1. Facial landmark detection result (NME) on DAD-3DHeads [34], FaceScape [64], and MultiFace [63]. Lower values mean better results.

Method	DAD-3DHeads [34]	FaceScape [64]	Multi-Face [63]
FAN [6]	7.141	16.74	16.143
Dlib [31]	10.841	29.431	18.205
3DDFA-V2 [23]	2.926	6.853	5.942
3DDFA [22]	4.082	7.988	8.121
3DDFA+	3.784	7.425	7.305
DAD-3DNet [34]	2.599	6.681	5.786
DAD-3DNet+	2.503	6.050	5.480

44,898 images collected from various sources (37,840 in the training set, 4,312 in the validation set, and 2,746 in the test set).

- **FaceScape** [64] is a large-scale high-quality lab-controlled 3D face dataset, which contains 18,760 examples, captured from 938 subjects and each with 20 specific expressions.

- **MultiFace** [63] is a new multi-view, high-resolution human face dataset collected from 13 identities for neural face rendering.

Training and Testing Split. In all the experiments, we only refine the baseline models with the training set of our DAD-3DHeads-Syn and their original training dataset. We use the test sets of DAD-3DHeads-Syn and DAD-3DHeads [34], and use the full datasets of FaceScape [64] and MultiFace [62] for performance evaluation. All the comparison methods have not been trained on the split test sets.

Evaluation Metrics. We evaluate the facial landmark distance by calculating the normalized mean error (NME). We normalize the landmark error by dividing its image resolution instead of the eye distance [54], since all the test set images are aligned with offline tools. We calculate the head

Table 2. Head pose estimation results (head pose error) on DAD-3DHeads [34], FaceScape [64]. Lower values mean better results.

	DAD-3DHeads [34]				FaceScape [64]			
	Pitch	Roll	Yaw	Overall	Pitch	Roll	Yaw	Overall
FAN [5]	9.765	5.376	6.390	7.177	8.774	4.895	6.556	6.742
Dlib [31]	13.352	11.799	14.654	13.268	17.861	12.663	19.548	16.691
3DDFA-V2 [23]	7.901	4.989	6.088	6.326	13.741	9.718	11.353	11.604
3DDFA [22]	9.895	7.977	8.996	8.956	20.789	18.145	19.692	19.752
3DDFA+	9.195	6.792	8.692	8.226	20.996	16.426	19.054	18.826
DAD-3DNet [34]	8.274	4.666	9.206	7.382	15.851	9.676	18.346	14.624
DAD-3DNet+	7.700	4.274	7.528	6.500	14.466	7.247	13.876	11.863

pose error by the absolute distance of the Euler angle values.

5.2. Quantitative Evaluation

Landmark Detection Results. The quantitative results of landmark detectionlandmark detection results on DAD-3DHeads [34], FaceScape [64], and MultiFace [63] are shown in Tab.1. We can find that the DAD-3DNet+ refined by our 3D-aware multi-view consistency training achieves the best performance in all three datasets. Moreover, according to the results of 3DDFA [22], 3DDFA+, DAD-3DNet [34], and DAD-3DNet+, we find that after refinement, the new models (3DDFA+ and DAD-3DNet+) achieve much better results than the baseline models. For example, the detection error of DAD-3DNet [34] drops 0.631 and 0.306 on FaceScape and MultiFace datasets, respectively, which are 9% and 5% improvements. Similarly, we improve the 3DDFA [22] by 0.298 (7%), 0.563 (7%), and 0.816 (10%) on DAD-3DHeads, FaceScape and MultiFace datasets, respectively. And we attribute the improvement to our proposed 3D aware multi-view training. One interesting phenomenon is that all the methods perform better on DAD-3DHeads dataset than the other two lab-captured datasets. We attribute this to the extreme head pose and challenging facial expressions in the other two datasets. We plot the head pose distribution of DAD-3DHeads (see supplementary materials) and find that balance of head pose is not as good as other two lab-controlled datasets.

Head Pose Estimation Results. Table.2 shows the head pose estimation error on DAD-3DHeads [34] and FaceScape [64]. Our DAD-3DNet+ achieves best performance in most metrics. Similar as the landmark results, we can also conclude that our 3D-aware multi-view consistency training improves the head pose detection of the baseline methods (3DDFA and DAD-3DNet) based on the comparison results in forth row (3DDFA vs. 3DDFA+) and fifth row (DAD-3DNet vs. DAD-3DNet+). For example, after refinement, DAD-3DNet+ achieves 11.9%[3] and 18.8%[4] performance boosts in overall head pose error on DAD-3DHeads and FaceScape dataset, respetively.

[3]Head pose error drops from 7.382 to 6.500.
[4]Head pose error drops 14.624 to 11.863.

5.3. Qualitative Evaluation

We fist show visual comparison on images randomly sampled from DAD-3DHeads testset [34] in Fig. 5. The landmark predicted by our DAD-3DNet+ model fits the individual's face tighter than other predictions. Furthermore, By comparing third column (3DDFA [22]) and forth column (ours), we can find that the updated model our 3DDFA+ improve the landmark accuracy dramatically. Similar visual improvement can be found in sixth (DAD-3DNet) and seventh (DAD-3DNet+) columns as well. If we closely look at the landmark results (sixth and seventh column), we can find the refinement training can drag the landmark and rotate it in 3D space to better fit it with the individual's face surface. We attribute this ability to our 3D-aware multi-view consistency training, which let the refined model gain the better sense in 3D space, therefor, improve the landmark detection results.

To further validate the improvement gained by the proposed 3D-aware multi-view consistency training, we show the visual results (Fig. 7) of 3DDFA [22], our refined 3DDFA+, DAD-3DNet [34], and our refined DAD-3DNet+ on images sampled from four different testsets. We can find that our proposed refinement improves the landmark detection results in eye, mouth, and face contour regions, which usually contain more appearance dynamics than other regions.

5.4. Performance Improvement Analysis

To systematically understand where is the improvement after refining the baseline methods (DAD-3DNet [34] and 3DDFA [22]) with our proposed 3D-aware multi-view consistency training, we further calculate and plot the landmark and head pose error improvements on DAD-3DHeads [34] (see Fig. 8). In stead of calculating the overall improved error score, we split all the testing images into different groups according to their head pose value and calculate the improved error score within each group. We can find that

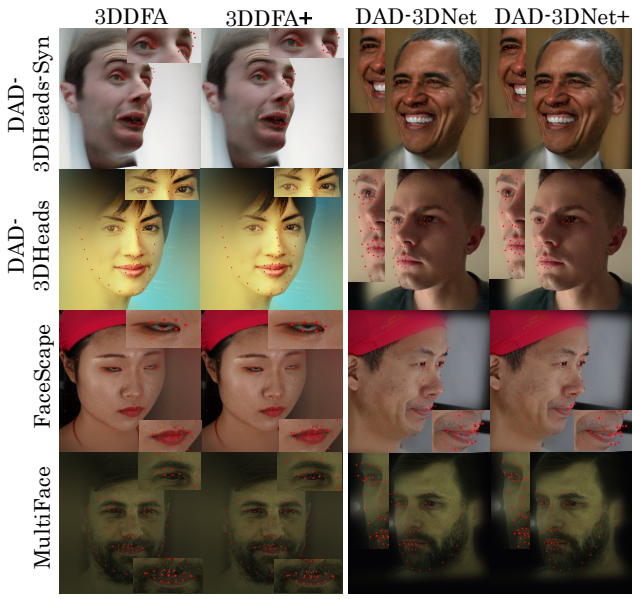

Figure 7. The visual comparisons between baseline methods and the refined methods on four testing sets. The left column and upper row list the dataset name and method name, respectively. '+' denotes the model that refined by our 3D-aware training.

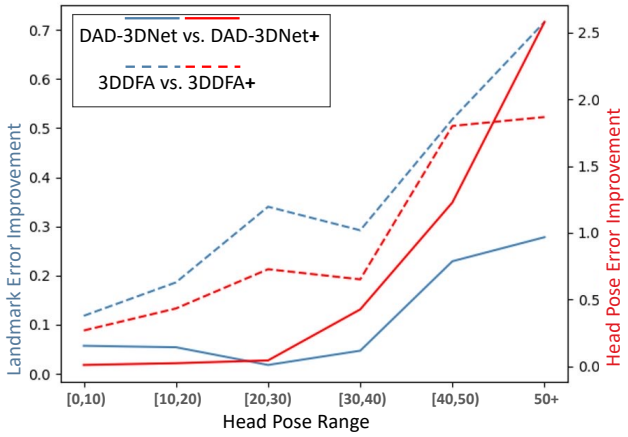

Figure 8. The landmark error and Head pose error improvement over DAD-3DNet [34] and 3DDFA [22] on images from different head pose ranges. The blue and red lines show the landmark error and head pose error improvement, respectively. The solid and dotted lines indicate DAD-3DNet [34] vs. DAD-3DNet+ (ours) and 3DDFA [22] vs. 3DDFA+ (ours).

the improvement by our training gets more obvious as the head pose gets more challenging. For example, the landmark error improvement (Fig. 8 blue part) using our method built on top of over 3DDFA [22] increases from 0.12 to 0.71. Similarly, the head pose estimation error (Fig. 6 ref part) improvement using our method built on top of DAD-3DNet [34] increases from 0.02 to 2.7. We also show the detection result visualization in Fig. 6. We can find that

Table 3. **Ablation Study on FaceScape [64]**

	Component	NME ↓	Pose ↓
1	full model (P=4)	**6.050**	**11.863**
2	w/o $\mathcal{L}_{\text{Mesh-Cons}}$	6.168	12.327
3	w/o $\mathcal{L}_{\text{Self-Cons}}$	6.541	13.623
4	full model (P=8)	**6.048**	**11.923**
5	full model (P=16)	6.098	11.902
6	full model (P=32)	6.139	11.912

from let to right, as the head pose increases, the error (ref line) of the DAD-3DNet+ (second row) is more stable than the error (first row) of the DAD-3DNet.

Base on this trend, we can conclude that our proposed 3D-aware multi-view consistency training improves more facial landmark detection and head pose estimation performance on images with larger head pose. This verifies our hypothesis that multi-view consistency training enable the network to learn 3D-aware information, therefor, benefiting the detection results on images with large head pose.

5.5. Ablation Study

We conduct ablation study on FaceScape [64] to verify the importance of main components of our novel design. As shown in Tab. 3, we calculate NME of landmark and MAE of pose estimation in these ablation experiments. Based on these numbers, we can see the performance degrades drastically when we remove $\mathcal{L}_{\text{Self-Cons}}$. Also, the role of $\mathcal{L}_{\text{Mesh-Cons}}$ is also verified crucial by the removal of it resulting suboptimal result. As to the number of view used in the 3D triangulation procedure, it helps to generate good results. Moreover, using less views to do the estimation of 3D landmark in world space is more timing efficient and speedup the fine-tuning process.

6. Conclusion

We propose 3D-Aware Multi-View Consistency training, a new framework for improving deep-learning base landmark detection algorithms. We propose a novel Self-Projection Consistency Loss to better learn the 3D-aware information, a novel dataset simulation pipeline to combine the merits of lab-controlled captures and in-the-wild collected images. The model refined by our method outperforms previous approaches in terms of landmark detection accuracy and head pose estimation accuracy. Admittedly, our work has some limitations. For example, our proposed training relies on the performance of the baseline method. If the pretrianed baseline yield poor initial predictions, our DLT would fail to estimate reasonable canonical 3D landmark, affecting the performance of the proposed self-projection consistency loss.

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