ACR Loss: Adaptive Coordinate-based Regression
Loss for Face Alignment

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Abstract—Although deep neural networks have achieved reasonable accuracy in solving face alignment, it is still a challenging task, specifically when dealing with facial images, under occlusion, or extreme head poses. Heatmap-based Regression (HBR) and Coordinate-based Regression (CBR) are among the two mainly used methods for face alignment. CBR methods require less computer memory, though their performance is less than HBR methods. In this paper, we propose an Adaptive Coordinate-based Regression (ACR) loss to improve the accuracy of CBR for face alignment. Inspired by the Active Shape Model (ASM), we generate Smooth-Face objects, a set of facial landmark points with fewer variations compared to the ground truth landmark points. We then introduce a method to estimate the level of difficulty in predicting each landmark point for the network by comparing the distribution of the ground truth landmark points and the corresponding Smooth-Face objects. Our proposed ACR Loss can adaptively modify its curvature and the influence of the loss based on the difficulty level of predicting each landmark point in a face. Accordingly, the ACR Loss guides the network toward more challenging points than easier points, which improves the accuracy of the face alignment task. Our extensive evaluation shows the capabilities of the proposed ACR Loss in predicting facial landmark points in various facial images.

I. INTRODUCTION

Face alignment, often known as facial landmark points detection, is the process of detecting and estimating the location of predefined key-points in facial images. Deep face alignment can be categorized into two methods: Coordinate-based Regression (CBR) [1]–[6], and Heatmap-based Regression (HBR) [7]–[11]. Although the HBR methods can achieve better accuracy, they are less efficient than CBR methods. To be more specific, while the output of the HBR methods are $k$ heatmap channels (where $k$ is the number of the landmark points), the output of CBR methods are the predicted landmark points, a $k$-dimensional vector. Thus, while the former requires complex post-processing, no post-processing is needed for the latter method. Moreover, CNNs that can be used as a backbone in CBR methods are mostly more efficient than CNNs that are used for the HBR methods since the models require greater number of model parameters to be capable of creating $k$ heatmap channel accurately.

Loss functions are an integral part of each deep learning model that can affect the performance of the network dramatically. We proposed a piece-wise loss function called ACR Loss designed to find the most challenging points during the training stage and guide the network to pay more attention to them. Inspired by the Active Shape Model (ASM) [12], we model a face object (the ground truth landmark points for a face) using the point-wise mean of all facial landmark points plus the shape-specific variation which is generated using the Eigenvectors of Covariance matrix (see Sec.III). Using more Eigenvectors will decrease the similarity between the mean face object and the ground truth face objects. We use this characteristic and for each face object, we consider the points with fewer similarities to the mean face as the most-challenging, and the points with the highest similarities as the least-challenging points (see Fig.1).

More clearly, for two different facial landmark points $p_1$ and $p_2$, if the distance between the location of $p_1$ and its corresponding point in Mean_Face object is smaller than the distance between $p_2$ and its corresponding point in Mean_Face object, prediction of the location of $p_2$ is more challenging than $p_1$. Considering this attribute, our proposed ACR Loss adapts its curvature to penalize the network for each landmark point in a face considering the hardness level of its prediction.

We use our proposed ACR Loss function to train 3 widely used CNNs, MobileNetV2 [13], EfficientNet-B0 [14], and EfficientNet-B3 [14] the challenging 300W dataset [15], and the Caltech Occluded Faces in the Wild (COFW) dataset [16]. Our experimental results show that the accuracy of face alignment using our novel ACR Loss significantly improves...
the performance of the CBR models compared to the widely used L2 loss. The contributions of this paper are:

- We propose a method to define the hardness level of each landmark point in a face object.
- We propose ACR Loss, which can adapt its curvature concerning the hardness level of each landmark point in a face. Accordingly, the magnitude and the influence of the loss are defined adaptively according to the hardness level of the landmark points.

The remainder of this paper is organized as follows. Sec. II reviews the related work in face alignment. Sec. III describes the proposed ACR Loss and how it improves the accuracy of face alignment task. Sec. IV provides the experimental results, and finally, Sec. VI concludes the paper with some discussions on the proposed method and future research directions.

II. RELATED WORK

Automated facial landmark points detection has been studied extensively by the computer vision community. Template-based fitting methods such as ASM [12] and AAM [17] are among the classical methods, where they aim to constrain the search space by using prior knowledge. Regression-based methods consider a facial image as a vector and use a transformation such as Principle Component Analysis (PCA), Discrete Cosine Transform (DCT) [18], or Gabor Wavelet [19], [20] to transform the image into another domain, then a classification algorithm such as Support Vector Machines (SVM) [21], [22] or boosted cascade detector [23] is used to detect facial landmarks.

**CBR methods:** Sun et al. [24] proposed a CNN using the cascaded deep convolutional network for face alignment. A coarse-to-fine auto-encoder networks (CFAN) proposed by Zhang et al. [25] for real-time face alignment. A cascaded coordinate regression method called the mnemonic descent method (MDM) proposed by Trigeorgis et al. [26] for facial landmark point detection. Xiao et al. [27] used a recurrent neural network while fusing the feature extraction and the regression steps and trained the network end-to-end. Two-Stage Re-initialization Deep Regression Model (TSR) [28] splits a face into several parts to ease the parts variations and regresses the coordinates of different parts. Valle et al. [29] proposed a simple CNN for better initialization to Ensemble of Regression Trees (ERT) regressor used for face alignment. Wingloss, introduced by Feng et al. [1], is a new loss function capable of overcoming the widely used L2-norm loss in conjunction with a pose-based data balancing (PDB). Zhang et al. [2] proposed a weakly-supervised framework to detect facial components and landmarks simultaneously. Ning et al. [8] proposed a new loss function to enhance the convergence of local regions. An attention distillation module proposed by Sadiq et al. [3] to infer the occlusion probability of each position in high-level features. Zhang et al. [5] proposed a group-wise face alignment dividing the landmark points into two stages, affine transformations and non-rigid distortions. Fard et al. [6] proposed a lightweight multi-task network for jointly detecting facial landmark points as well as the estimation face pose. KD-Loss [30] proposed a knowledge distillation-based architecture for face alignment.

**HBR methods:** Yang [31] proposed a two-part network including a supervised transformation to normalize faces, as well as a stacked hourglass network [32], which is designed to predict heatmaps. HRNet [33], a high-resolution network applicable in many Computer Vision tasks such as facial landmark detection, achieves a reasonable accuracy. Liu et al. [10] proposed an attention-guided coarse-to-fine network, which is guided to emphasize key information while suppressing less important information. In addition, Irannanneh et al. [34] proposed an approach to provide a robust face alignment algorithm that copes with shape variations by aggregating a set of manipulated images to capture a robust landmark representation. Park et al. [35] proposed a complementary regression network to combine both global and local regression methods for face alignment. An encoder-decoder CNN et al. [36] uses a cascade of CNN regressors to increase the accuracy of the face alignment task. Wu et al. [11] used a lightweight U-Net model and a dynamic optical flow to obtain the optical flow vector of the landmark and uses dynamic routing to improve landmark stabilization. To improve the tolerance of the face alignment toward the occlusion, Park et al. [37] combined a coordinate regression network and a heatmap regression network with spatial attention.

Although heatmap-based models achieve better results than coordinate-based models, they perform poorly in terms of inference time, computational complexity, and memory consumption. On the contrary, the coordinate-based models do not require any post-processing operations. Hence, since the efficiency of the model is a key factor in this paper, we train 3 different models one using L2 and one using our proposed ACR Loss. We show in Sec.IV that using ACR Loss improves the performance of face alignment compared to the widely used L2 loss.

III. PROPOSED ACR LOSS

In this section, we first discuss the issues with the previously proposed loss functions which are used in order to train the CBR methods, L2, and L1 losses. We then present our proposed ACR Loss and show its effectiveness in improving the performance of CBR face alignment.

A. Issues with the Current CBR Loss Functions

The loss function and the magnitude of its gradient (aka the influence) of the loss function, are the two attributes that we analyze in our investigation.

For \( L2 \) loss \((y = x^2)\), the magnitude of the gradient is \( |x| \). Accordingly, The influence of the loss function depends on the magnitude of the error. Therefore, the influence of the loss function on the network is large for large errors while it is small for small errors. The optimization problem for a single landmark point is solvable using Stochastic Gradient Descent (SGD) or numerical methods. However, when it comes to the optimization of \( M \times b \) facial landmark points \(-M\) is the number of facial landmark points defined for each input
image, and $b$ is the size of the mini-batch—, the accumulative influence of the large errors on the loss function can be more significant than the influence of the small errors. Hence, the loss function might only focus on localizing the landmark points with large errors while ignoring the points with small errors. This characteristic of $L_2$ loss can negatively affect the performance of facial landmark localization and result in an inaccurate prediction.

For $L_1$ loss ($y = |x|$), the magnitude of the gradient is 1, indicating that the influence of the loss is agnostic to the magnitude of the error. Although $L_1$ loss does not have the above-mentioned issue of $L_2$ loss, its indifference on the magnitude of the errors affects the optimization process negatively, meaning that the training of the model requires more steps to converge to the optimal solution.

To tackle the weaknesses of $L_2$ and $L_1$ loss functions, we propose a piece-wise loss function which is logarithmic ($y = \ln(|x|^2 - \Phi + 1)$) for small errors and quadratic for large errors. Moreover, we define $\Phi \in [0, 1]$ such that it is larger for challenging points compared to points which are easier for the network to be predicted (see Sec.III-B). Accordingly, $\Phi$ modifies the curvature of the loss function to adapt the loss magnitude and the influence of the loss on the model for each facial landmark point according to its hardness of prediction for the model. Thus, for the challenging points where $\Phi \approx 1$, the logarithmic piece of the ACR Loss is $y \approx \ln(|x| + 1)$, while for the less challenging ones ($\Phi \approx 0$) it is $y = \ln(x^2 + 1)$ (see Fig 2). Typically, for each landmark point that exists in a face, we define the corresponding weight, $\Phi$, which is used to adapt the influence of the logarithmic part. Hence, instead of only considering the magnitude of the errors (the distance between the ground truth and the predicted landmark point) to design the loss function, we define a metric to measure how challenging a landmark point is and adapt the loss curvature accordingly.

The gradient of the logarithmic part for $\Phi \approx 1$ is $y' = \frac{1}{1+|x|}$ which means the influence of the loss increases as the errors become smaller. Consequently, contrary to $L_2$ loss (where the influence of the loss reduces as the magnitude of the error decreases), the ACR Loss is designed to guide the network to pay more attention to the localization of the challenging points no matter how small the magnitude of the error is. On the contrary, for less challenging landmark points, where $\Phi \approx 0$, the gradient of the logarithmic part is $y' = \frac{2|x|}{1+x^2}$. Therefore, as the error decreases the influence of the loss decreases too.

We show in Sec.IV that this characteristic of the ACR Loss enables it to perform more accurately in face alignment tasks compared to the widely used $L_2$ loss.

### B. ACR Loss

Inspired by ASM [17], we define a Face object using an $M$-dimensional vector in the following Eq. 1:

$$
\text{Face}_{M \times 1} \approx \text{Mean_Face}_{M \times 1} + V_{M \times k} b_{k \times 1}
$$

where $M$ is the number of facial landmark points defined for each image, $\text{Mean_Face}$ object is the mean shape object created by calculating the point-wise mean of all facial landmark points in the training set. In addition, $V = \{v_1, v_2, \ldots, v_k\}$ contains $k$ Eigenvectors of the Covariance matrix created from all samples in the training set. In addition, $b$ is a $k$ dimensional vector given by Eq. 2:

$$
b_{k \times 1} = V_{k \times M}^T (\text{Face}_{M \times 1} - \text{Mean_Face}_{M \times 1})
$$

Considering that the statistical variance (i.e., Eigenvalue) of the $i^{th}$ parameter of the vector $b$ is $\lambda_i$. To make sure the generated shape object after applying ASM (i.e., approximating a face object using Eq. 1) is relatively similar to their corresponding ground truth, the parameter $b_i$ of vector $b$ is usually limited to $\pm 3\sqrt{k}$ [38]. Then, we define the Smooth_Face object as follows in Eq. 3:

$$
\text{Smooth_Face}_{M \times 1} = \text{Mean_Face}_{M \times 1} + V_{M \times k} b_{k \times 1}
$$

We define $l \in \{0, 1, \ldots, k\}$ indicates the number of the Eigenvectors we use to create the Smooth_Face object.

The number of the Eigenvectors that we choose for creating Smooth_Face object defines the similarity between the original face object (the ground truth face) and the generated Mean_Face object. In other words, if we define the number of the Eigenvectors (or the parameter $l$ in Eq. 1) equal to 0, Smooth_Face object will be the same as Mean_Face object. Likewise, if we use all the Eigenvectors, the generated Smooth_Face object will be the same as the original Face, and thus having the least similarity to Mean_Face object.

Since the variation of Smooth_Face object is less than the ground truth face object, --as a rule of thumb-- it is easier for the network to learn the distribution of Smooth_Face object compared to the distribution of Face. We use this characteristic to propose our ACR Loss. The main idea of the ACR Loss is to find the most challenging landmark points for each input image and penalize the model more by changing the loss curvature adaptively for such points compared to less challenging points. For each input image, we use the distance between each landmark point and the corresponding points in Smooth_Face object as a metric that indicates how challenging a landmark point is. For an input image $img_i$ the ground truth face object $Face_i$, and the corresponding smooth face $\text{Smooth_Face}_i$, we define $\Phi_{i,m}$ as follows in Eq. 4:

$$
\Phi_{i,m} = \frac{|\text{Smooth_Face}_{i,m} - \text{Face}_{i,m}|}{\max(|\text{Smooth_Face}_{i,q} - \text{Face}_{i,q}|) \forall q \in M}
$$

such that $\text{Face}_{i,m}$ is the $m^{th}$ landmark points of the $i^{th}$ sample in the training set. We use $\Phi_{i,m}$ as a weight indicating how challenging is a landmark point, and accordingly adapt the loss curvature to declare the magnitude and the influence of the loss. Then, we define our ACR Loss in Equations 5, 6, 7:

$$
\Delta_{i,m} = |\text{Face}_{i,m} - \text{Pr_Face}_{i,m}|
$$

$$
\text{loss}_{\text{face}}_{i,m} = \begin{cases} 
\lambda \ln(1 + \Delta_{i,m}^2 - \Phi_{i,m}^2) & \text{If: } \Delta_{i,m} \leq 1 \\
\Delta_{i,m}^2 + C & \text{If: } \Delta_{i,m} > 1
\end{cases}
$$
Fig. 2. The proposed ACR Loss for a single landmark point. In each figure, we depicts the ACR Loss curvature for \( \Phi \) as equal to 0, 1, 2. Besides, we depict the ACR Loss curvature for different values of the hyper-parameter \( \lambda \) as well.

\[
\text{Loss}_{ACR} = \frac{1}{M N} \sum_{i=1}^{N} \sum_{m=1}^{M} \text{loss}_{\text{face}}(\phi_{i,m})
\]  

(7)

where, \( M \) and \( N \) are the numbers of the landmark points and images in the training set, respectively. \( Pr_{\text{face}_{i,m}} \) is the \( m^{th} \) landmark point of the \( i^{th} \) the predicted face object, and \( C = \Phi_{i,m} \ln(2) - 1 \) is a constant defined to link the quadratic part to the logarithmic part smoothly. In addition, the hyper-parameter \( \lambda \) is defined to adjust the ACR Loss curvature (see the ablation study, Sec V-C, for the effect of the different value of \( \lambda \) on the performance of the face alignment task.)

As Fig. 2 depicts, we define the ACR Loss as a piece-wise function to make it cope well with both small and large errors. For the large errors (where \( \Delta_{i,m} \) is greater than 1), we define the ACR Loss to be a quadratic function. Accordingly, the magnitude and the influence of the loss function rely upon the magnitude of the error. For small errors (where \( \Delta_{i,m} \) is lower than or equal to 1), we modify the loss curvature according to the value of \( \Phi_{i,m} \), which indicate the hardness level of the prediction of the corresponding point. Accordingly, for the challenging points, the value of \( \Phi_{i,m} \) is close to zero, the magnitude of the loss and its influence decrease as the value of the error decreases. In contrast, for the challenging points, the value of \( \Phi_{i,m} \) is close to 1 and accordingly, the ACR Loss becomes a logarithmic loss function. Consequently, the influence of the loss function increases as the value of the error decreases.

In addition, in L2 loss the magnitude of the loss value only relies on the prediction error, which is the distance between a ground truth facial landmark point and its corresponding predicted point. Therefore, the greater the prediction error, the greater the loss value. Consequently, L2 loss is less sensitive to small errors compared to the large errors.

To cope with this issue, for each landmark point \( P_y \), we define \( \Phi \) as the distance between the landmark point \( P_x \) in Smooth_Face object and the corresponding landmark point \( P_y \) in the ground truth set. \( \Phi \) can modify the curvature of the ACR Loss, so the magnitude of the loss is set based on the hardness of the prediction of \( P_y \) for the network. Consequently, the ACR Loss guides the model to pay more attention to localizing the challenging points which results in accuracy improvement.

The number of the Eigenvectors (or the parameter \( k \)) defines the similarity between the ground truth face object and the corresponding Smooth_Face. In the very first epochs during the training, the predicted face objects are similar to the Mean_Face object. Then, gradually the model learns the face-specific features so that the predicted facial landmark point becomes more similar to their corresponding ground-truth points. Accordingly, we increase the number of the Eigenvectors for creating the Smooth_Face objects. In other words, as the prediction accuracy of the model increases during the training, we need to add more face-specific variations (see Eq.3) to the generated Smooth_Faces to make sure that \( \Phi_{i,m} \) represent the most challenging points. Empirically we choose \( k \) to be \( k = 80\% \) of all the available Eigenvectors from epoch 0 to 15, \( k = 85\% \) from epoch 16 to 30, \( k = 90\% \) from epoch 31 to 70, \( k = 95\% \) from epoch 71 to 100, and \( k = 97\% \) from epoch 101 to 150. So, in the very first epochs, we update \( k \) faster comparing to the last epochs since on the last epochs the network required more effort to predict the facial landmark points more accurately.

C. ACR Loss Optimization

We use SGD algorithm to optimize our proposed ACR Loss. Based on the Eq. 7 (and as also Fig. 2 shows), the quadratic piece of ACR Loss is a convex function, while the logarithmic piece is a concave function. Although the concave piece may
cause the optimization to be unstable, as Feng et al. [1] shows, a logarithmic loss function for coordinate-based regression landmark localization task does not have any negative effects on the optimization. We calculate the gradient of our piece-wise ACR Loss in Eq.8:

\[
\nabla Loss_{ACR} = \begin{cases} 
\frac{\Delta (\Phi - 2)}{\Delta^2} & if: \Delta \leq 1 \\
\frac{\Delta (\Phi - 2)}{\Delta^2} & if: \Delta > 1
\end{cases}
\]

(8)

Accordingly, for \( \Delta > 1 \) part, the derivative of the loss function is \( 2 \Delta \) which is differentiable on its domain of definition, and SGD can find its optimal minimum. As Fig.3 depicts, for \( \Delta \leq 1 \) part, the gradient function is \( \frac{\Delta (\Phi - 2)}{\Delta^2} \). Therefore, for \( \Phi = 0 \), the gradient of the loss is \( \frac{1}{\Delta^2} \), a differentiable function in its domain of definition. Likewise, for \( \Phi = 1 \), the gradient of the loss is \( \frac{1}{\Delta^2} \), which is differentiable in its domain of definition as well. Thus, SGD is capable of finding its optimal minimum.

IV. EXPERIMENTAL RESULTS

For the ease of use, we define \( MN_{ACR} \), \( EF-0_{ACR} \), and \( EF-3_{ACR} \) which are MobileNetV2 [13], EfficientNet-B0 [14], and EfficientNet-B3 [14] being trained using our ACR Loss versus the corresponding \( MN_{base} \), \( EF-0_{base} \), and \( EF-3_{base} \) being trained using the widely used L2 loss. We uses 300W [15], and COFW [16] dataset for our experiments.

V. IMPLEMENTATION DETAILS

For the training set in each dataset, we cropped all the images and extract the face region. Then the facial images are scaled to 224 \( \times \) 224 pixels. We augment the images (in terms of contrast, brightness, and color) to add robustness of data variation to the network. We train networks for about 150 epochs, using the Adam optimizer [39] with a learning rate of \( 10^{-3} \), \( \beta_1 = 0.9 \), \( \beta_2 = 0.999 \), and decay \( = 10^{-5} \) on a NVidia 1080Ti GPU.

A. Evaluation on COFW

As shown in Table I, for the COFW [16] dataset, using MobileNetV2 [13] as the network, the NME and FR reduce 1.15\% (from 4.93 to 3.78) and 0.2\% (from 0.59\% to 0.39\%) respectively, and ACU increases about 8.77\% from 0.7338 to 0.8215 while we train the model using ACR Loss. Likewise, using EfficientNet-B0 [14] as the backbone network, we see that both NME and FR fell from 4.93\% to 4.20\% (0.73\% reduction), and from 1.18\% to 0.59\% (0.59\% reduction) respectively, and ACU rises about 5.59\% from 0.7333 to 0.7892. As well as that, using EfficientNet-B3 [14], we also face about 0.24\% (from 3.71\% to 3.47\%) reduction on NME, while AUC increases from 0.8275 to 0.8421, about 1.46\%.

Table II shows the results of the state-of-the-art methods as well as \( EF_3_{ACR} \), the EfficientNet-B3 [14] trained using our proposed ACR Loss. As shown in Table II, the NME of \( EF_3_{ACR} \) is 3.47\%, which is the lowest among the state-of-the-art methods. In addition, the FR of our method is 0.39\%, which equals to the FR of LAB [7] and the lowest as well.

Fig 4 shows some samples of face alignment using ACR Loss compared to l2 loss.
TABLE III

NME (IN %) OF 68-POINT LANDMARKS LOCALIZATION ON 300W [15] DATASET.

| Method      | Common | Challenging | Fullset |
|-------------|--------|-------------|---------|
| FARN [42]   | 4.25   | 7.55        | 4.88    |
| SAN [44]    | 3.34   | 6.60        | 3.98    |
| LAB [7]     | 2.98   | 5.19        | 3.49    |
| ODN [43]    | 3.56   | 6.67        | 4.17    |
| HORNet [45] | 3.38   | 6.36        | 3.96    |
| CHR2c [36]  | 2.85   | 5.15        | 3.30    |
| mnv2KD [30] | 3.56   | 6.13        | 4.06    |
| EF-3ACR (ours) | 3.36   | 3.36        | 3.15    |

Challenging subset of the 300W [15] dataset. To be more comparable to the state-of-the-art methods specifically on the 5 ACN Loss compared to L2 loss.

B. Evaluation on 300W

Table I shows that on the Challenging subset of 300W [15] dataset, training the networks using ACR Loss results in about 1.16% (from 7.32% to 6.16%), 0.21% (from 6.92% to 6.71%) and 0.65% (from 6.01% to 5.36%) reduction in NME using MobileNetV2 [13], EfficientNet-B0 [14], and EfficientNet-B3 [14] as the network respectively. Similarly, the FR decreases about 11.11% (from 12.50% to 1.48%) for MobileNetV2 [13], about 2.96% (from 7.40% to 4.44%) EfficientNet-B0 [14], while it remains without any change for EfficientNet-B3 [14]. Moreover, The AUC increase about 11.23% (from 0.4953 to 0.6076), 1.98% (from 0.5228 to 0.5426) and 6.42% (from 0.6196 to 0.6838), using MobileNetV2 [13], EfficientNet-B0 [14], and EfficientNet-B3 [14] as the network respectively and train the models using ACR Loss compared to L2 loss.

As Table III shows, the performance of the EF-3ACR is comparable to the state-of-the-art methods specifically on the Challenging subset of the 300W [15] dataset. To be more specific, on the Challenging subset, while the lowest NME, 5.15%, achieved by CHR2c [36], EF-3ACR achieves 5.36%, which is much better than many recently-proposed methods for face alignment. Accordingly, we can conclude that ACR Loss performs much better in localizing the faces under challenging circumstances such as occlusions, extreme pose, and illumination. Moreover, Table IV presents the NME of the lightweight state-of-the-art models with MNACR, which is MobileNetV2 [13] trained using ACR Loss. According to the Table IV, MNACR achieves by far the best performance. Fig 4 shows samples of face alignment using ACR Loss comparing to L2 loss.

C. Ablation Study

As Fig2 depicts, the parameter λ in Eq 6 can adjust the curvature of the ACR Loss. Typically, by increasing the value of λ, the magnitude of the ACR Loss function increases as well. We conducted 6 experiments to study the effect of the different values of the hyper-parameter λ on the accuracy of the face alignment. In our experiments, we use EfficientNet-B3 [14] as the model, and conduct the experiments on 300W [15] dataset.

For the Common and Full subsets, defining λ to be in {1, 2, 3} does not affect the NME of the face alignment too much. To be more detailed, for λ = 1, the NME on the "Common" subset is 3.59%, while it reduces to 3.51% for λ = 2, and then increases to 3.56% for λ = 3. In contrast, for the Challenging subset, increasing the value of λ from 1 to 4 results in reduction in the NME from 3.56% (for λ = 1) to 5.36% (for λ = 4). Similarly, on the Common and Full subsets the minimum value of the NME achieved by defining λ = 4. Then, we continue increasing the value of λ to be 5 and then 10. As Fig2 shows, the NME goes up on all subsets as we increase the value of λ to be 4. Likewise, increasing λ to 10 worsen the accuracy and the NME goes up to its maximum in the experiment range. Therefore, according to our experiments we define λ = 4 since it results in the least NME value.

VI. CONCLUSION AND FUTURE WORK

This paper proposed an adaptive piece-wise loss function called ACR Loss. Comparing the face objects with their corresponding smoothed versions, we define a metric that indicates how challenging the prediction of a landmark point for the CNN is. Thus, for each landmark point, while L2 loss just uses the magnitude of the error to define the magnitude of the loss, ACR Loss adapts its curvature to set the loss influence and its magnitude based on the hardness of the landmark points. ACR Loss is capable of guiding the network towards focusing on the more challenging points, having the least similarity to their corresponding Smooth-Face, compared to the less challenging points, having the highest level of similarity to their corresponding Smooth-Face. For further study, we plan to use our proposed loss function in other computer vision tasks such as human body joint tracking.
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