Beyond Disentangled Representations: An Attentive Angular Distillation Approach to Large-scale Lightweight Age-Invariant Face Recognition

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Abstract—Disentangled representations have been commonly adopted to Age-invariant Face Recognition (AiFR) tasks. However, these methods have reached some limitations with (1) the requirement of large-scale face recognition (FR) training data with age labels, which is limited in practice; (2) heavy deep network architecture for high performance; and (3) their evaluations are usually taken place on age-related face databases while neglecting the standard large-scale FR databases to guarantee its robustness. This work presents a novel Attentive Angular Distillation (AAD) approach to Large-scale Lightweight AiFR that overcomes these limitations. Given two high-performance heavy networks as teachers with different specialized knowledge, AAD introduces a learning paradigm to efficiently distill the age-invariant attentive and angular knowledge from those teachers to a lightweight student network making it more powerful with higher FR accuracy and robust against age factor. Consequently, AAD approach is able to take the advantages of both FR datasets with and without age labels to train an AiFR model. Far apart from prior distillation methods mainly focusing on accuracy and compression ratios in closed-set problems, our AAD aims to solve the open-set problem, i.e. large-scale face recognition. Evaluations on LFW, IJB-B and IJB-C Janus, AgeDB and MegaFace-FGNet with one million distractors have demonstrated the efficiency of the proposed approach. This work also presents a new longitudinal face aging (LogiFace) database for further studies in age-related facial problems in future.

Index Terms—Age-Invariant Face Recognition, Attentive Angular Distillation, Teacher-Student Network

I. INTRODUCTION

The research in Age-invariant Face Recognition (AiFR) has gained considerable prominence lately due to the challenges in the nature of human aging and the demand of consistent face recognition algorithms across ages. Indeed, such AiFR algorithms are important in practical applications where there is a significant age difference between probe and gallery facial photos, such as passport verification or missing children identification. However, compared to the state-of-the-art results of stand-alone Face Recognition (FR) algorithms, the performance of AiFR is still very limited due to the lack of robustly identifiable features stable across ages. In addition, these AiFR algorithms are often evaluated separately from stand-alone FR algorithms although they are used together in practice.

Disentangled learning representations have been used widely in AiFRs, but however have reached some limitations. Firstly, in order to achieve a high accuracy performance, these AiFR methods often adopt heavy deep network architectures with the support of GPU platforms. Then, they require a large-scale FR training set (i.e. multiple images per subject) with manual age labels. However, this type of dataset is very limited in real-world. Indeed, there are many large-scale training face databases without age labels in practice, but unusable for training these AiFR models. These disentangled learning based AiFR methods usually assume that the relationship between the identification and the age attributes can be linearly factorized in a latent or deep feature space. Furthermore, these prior AiFRs are usually evaluated against age-related face databases, but have not compared against other standard large-scale AiFR benchmarks to guarantee the robustness of the algorithms.

By addressing aforementioned limitations, this work presents a novel Attentive Angular Distillation (AAD) approach to Large-scale Lightweight AiFR. Particularly, in order to alleviate the heaviness of a deep network structure while maintaining its accuracy, a Knowledge Distillation framework with two teachers (i.e. heavy high-performance networks) of different specialized knowledge is introduced. One teacher masters the FR task while the other tackles the age estimation task. Then, the attention knowledge about age-invariant facial regions (as shown in Fig. 1) and feature

Fig. 1. Deep Attention Heat-maps on Age-invariant Regions.

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*This database will be made available

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discriminative power from these teachers are distilled to the student via the proposed AAD. Consequently, the lightweight student network can naturally and effectively be beneficial from the knowledge of both teachers and become more powerful in both tasks. Intuitively, with the knowledge from age estimation teacher, the student is guided to focus on the facial regions that are robust against age changes, while it is taught by the other teacher to achieve high accuracy on FR task. Then by generalizing these knowledge during training process, the student can be further improved for AiFR task.

**Contributions.** This paper introduces an AAD framework for AiFR. The contributions of this work are five-fold. (1) We proposed a novel *Age-Invariant Attentive Distillation and Angular Distillation Losses* for distilling both age-invariant attention and feature direction from various teachers to the student. Since the teachers for different tasks are efficiently obtained by the databases of those specific tasks, our AAD framework is able to take the advantages of both face recognition datasets with and without age labels to train the models to generalize million-scale subjects. (2) Although angular metric has been recently used quite successfully in face recognition, it hasn’t been discovered in network distillation problems. Our method presents to look at the Angular under a new point of view when it is used to translate the learned knowledge. (3) Unlike prior distillation methods that mainly focus on closed-set problems with one or several teacher(s) of the same task, our proposed distillation solution is proved to be even robust in the open-set problems, i.e. large-scale face recognition. (4) The proposed AAD approach not only achieves state-of-the-art performance on AiFR databases but also is highly competitive against state-of-the-art face recognition methods on the standard large-scale face recognition benchmarks. (5) Finally, this work introduces a new longitudinal face aging (LogiFace) database that will be made publicly available for further studies in age-related facial problems in future. To the best of our knowledge, this is one of the first AiFR approaches that allow the use of training face databases with and without age labels together.

### II. Related Work

#### A. Age Invariant Face Recognition

Many previous works [13], [15], [14], [16], [17], [18], [19], [20], [21], [31], [32] explored the face invariant features from hand-craft features designed by heuristic to deep features learned by deep neural networks. Juefei-Xu et. al. [16] presented a framework which utilizes the periocular region for age invariant face recognition. Gong et. al. [14] introduced a Hidden Factor Analysis (HFA) approach to decomposes the latent face representation into age-invariant and age-sensitive latent factors and optimized using EM frameworks. Yandong et. al. [21] later introduced and improved version of HFA by using the deep convolutional neural network guided by Latent Factorization. Xu et. al. [21] developed a coupled Auto-Encoder and a non-linear analysis factorizing identity feature from the face representation. Wang et. al. [20] proposed Orthogonal Embedding CNNs (OE-CNNs) decomposing deep face features into two orthogonal ID and Age components based on the directions in angular space and radial space. Wang et. al. [19] proposed Decorrelated Adversarial Learning (DAL) algorithm utilizing the Batch Canonical Mapping Module to find the maximum correlation between the identity features and age features [34], [35], [36], [37] generated by a deep network.

#### B. Knowledge Distillation

The approaches in this direction aim at learning a lightweight network (i.e. student) such that it can mimic the behaviors of the heavy one (i.e. teacher). With the useful information from the teacher, the student can learn more efficient and be more “intelligent”. One of the first knowledge distillation works was introduced by [33] suggesting to minimize the $\ell_2$ distance between the extracted features from the last layers of these two networks. Hilton et. al. [31] later pointed out that the hidden relationships between the predicted class probabilities from the teacher are also very important and informative for the student. Then, the soft labels generated by the teacher model are adopted as the supervision signal in addition to the regular labeled training data during the training phase. Romero et. al. [21] bridged the middle layers of the student and teacher networks and adopted $\ell_2$ loss to further supervised output of the student. Several other aspects and knowledge of the teacher network are also exploited including feature activation map [7], feature distribution [8], block feature flow [9], Activation-based and Gradient-based Attention Maps [3], Jacobsians [5], Unsupervised Feature Factors [6]. Recently, Guo et al. [9] proposed to distill both prediction scores and gradient maps to enhance the student’s robustness against data perturbations. Other knowledge distillation methods [4], [39], [40], [41].

### Table I

| Method         | Object Class | Teacher Transform | Student Transform | Distilled Knowledge                      | Loss Function | Missing Info |
|----------------|--------------|-------------------|-------------------|-----------------------------------------|---------------|--------------|
| KD [1]         | Closed-set   | Identity          | Identity          | Logsits                                 | $\ell_{CE}$   | x            |
| FitNets [2]    | Closed-set   | Attention         | Attention         | Activation/Gradient Map                  | $\ell_2$     | ✓            |
| Att_Trans [3]  | Closed-set   | Correlation       | Correlation       | Jacobians                               | $\ell_2$     | ✓            |
| DNN_FSP [4]    | Closed-set   | Gradient          | Gradient          | Jacobians                               | $\ell_1$     | ✓            |
| Factor_Trans [5]| Closed-set   | Encoder           | Encoder           | Feat. Factors                           | $\ell_1$     | ✓            |
| Activation_Bound [6]| Closed-set | Binarization      | $1 \times 1$ conv | Activation Map                          | Marginal $\ell_2$ | ✓           |
| AL_PSN [7]     | Closed-set   | Identity          | Identity          | Feature Distribution                    | $\ell_{GAN}$  | ✓            |
| Robust_SNLI [8]| Closed-set   | Identity          | Scores + Gradient | Jacobians                               | $\ell_2$     | ✓            |

*Ours* | Open-set | Identity | $1 \times 1$ conv | Direction | Angular | ✓ |

*Table I: The comparison of the properties between our distillation approach and other methods. $\ell_{CE}$ denotes the cross-entropy loss.*
are also proposed for variety of learning tasks. Although these methods have achieved prominent results, most of them are proposed for closed-set problems with one or more teachers of the same task. In our work, we propose to distill the information from two teachers of different tasks to make the student more powerful with the desired property.

III. OUR PROPOSED AAD METHOD

In order to enhance the student with age-invariant capability while preserving a high accuracy on standard FR, two types of knowledge including Age-invariant Attentive and Angular Knowledge are exploited from different teachers. This knowledge is then transferred to the student through Attentive and Angular Distillation procedures as shown in Fig. 2a. In this way, the first component guides the student to pay more attention to facial regions that are robust against changes across ages, while the second component can teach and supervise its student to obtain the effective final solutions.

Formally, let \( T^R, T^A, S : \mathcal{I} \rightarrow \mathcal{Z} \) define the mapping functions from an image domain \( \mathcal{I} \) to a high-level embedding domain where \( T^R, T^A \) are teacher networks and \( S \) is the student network. All functions \( T^R, T^A \) and \( S \) are the compositions of \( n \) sub-functions as.

\[
T^R(I; \Theta^r) = [T_1^R \circ T_2^R \circ \ldots \circ T_n^R](I, \Theta^r)
\]

\[
T^A(I; \Theta^a) = [T_1^A \circ T_2^A \circ \ldots \circ T_n^A](I, \Theta^a)
\]

\[
S(I; \Theta^s) = [S_1 \circ S_2 \circ \ldots \circ S_n](I, \Theta^s)
\]

(1)

where \( I \) denotes the input image, \( \circ \) is the function composition notation, \( \{\Theta^r, \Theta^a, \Theta^s\} \) are the parameters of \( \{T^R, T^A, S\} \), respectively. Then given two high-capacity functions \( T^R \) and \( T^A \) (i.e. teachers), the goal of model distillation is to distill the knowledge from \( T^R \) and \( T^A \) to a limited-capacity function \( S \) (i.e. student) so that \( S \) can embed a similar latent domain as \( T^R \) with an additional desired features of \( T^A \). To achieve this goal, the learning process of \( S \) is usually taken place under the supervision of \( T^R \) and \( T^A \) by comparing their outputs via

\[
L_{\text{distill}} = \sum_{i}^{n} \lambda_i L_i(S, T^R, T^A) \]

where

\[
L_i(S, T^R, T^A) = \sum_{T \in \{T^R, T^A\}} d(G^T_i(F^R_i), G^T_i(F^a_i); T)
\]

\[
F^R_i = [T_1 \circ T_2 \circ \ldots \circ T_n](I, \Theta^r), t \in \{t_a, t_a\}
\]

\[
F^a_i = [S_1 \circ S_2 \circ \ldots \circ S_n](I, \Theta^s)
\]

(2)

where \( G^T_i(\cdot) \) and \( G^T_i(\cdot) \) are transformation functions of \( T \) and \( S \); these transformations make their corresponding embedded features comparable. \( d(\cdot, \cdot) \) denotes the difference between these transformed features. It is worth noting that the form of \( L_i(S, T^R, T^A) \) provides two important properties. Firstly, since \( d(\cdot, \cdot) \) measures the distance between \( F^R_i \) and \( F^a_i \), it implicitly defines the knowledge to be transferred from \( T \) to \( S \). Secondly, \( G^T_i(\cdot) \) and \( G^T_i(\cdot) \) control the portion of the transferred information. The next sections focus on the designs of these two components for selecting the most informative features and transferring them to the student.

A. Age-invariant Attention from Teacher

Generally, among the informative knowledge that can be exploited from the teacher, the attention mechanism \([44, 45, 46, 47] \) to make decisions is one of the key aspects to enhance the power of a teacher as well as improve the knowledge of student \( S \). This is also consistent with our visual experience where attention information is important for human to possess details and coherence. Therefore, in this section, we propose an attentive distillation process making the student \( S \) enhanced with desired properties, especially the age-invariant factor. Particularly, to obtain the age-invariant property for \( S \), in the simplest approach, one can derive a teacher function with that capability (i.e. map the input image \( I \) to an age-invariant latent feature space) and exploit the attention information from that teacher. However, obtaining this teacher function is not an easy task. Although some previous disentangled learning approaches have been introduced in literature \([14, 19, 20] \), most of them rely on the assumption that ID and age attributes can be linearly factorized in embedding.
domain. Moreover, the training data for these approaches are still limited. Meanwhile, we argue that this goal can still be practically achieved from an alternative teacher who can show its student about age-sensitive regions of the face. From that instruction, the student can generalize its knowledge by adaptively paying more attention to the remaining face regions to reduce the sensitivity to age factor.

**Age-Sensitive Attentive Knowledge.** Formally, let $T^A$ be a teacher function mapping the input image $I$ to the latent features used to predict the age of a subject in $I$. An attentive mapping function $A^T_i(\cdot)$ with respect to a feature map $F^{t_{sa}}_i$ can be defined as $A^T_i : \mathbb{R}^{c_i \times h_i \times w_i} \mapsto \mathbb{R}^{h_i \times w_i}$, where each value in $A^T_i$ indicates the importance of the corresponding entry in $F^{t_{sa}}_i$. In other words, the function $A^T_i$ aims to validate the contributions of each local region in $F^{t_{sa}}_i$ to the discriminative power of the final representation of $T^A$. Then by looking at the regions with higher importance, we can efficiently extract the knowledge of where $T^A$ pays attention in each stage of its embedding process. Intuitively, since $T^A$ aims to discriminate the age factor presented in $I$, its embedding process will naturally focus on the age-sensitive facial regions and automatically enhance the importance of these regions with higher intensity values for $F^{t_{sa}}_i$. This type of information can be considered as the age-sensitive attentive knowledge and extracted via the statistics across $c_i$ channels of $F^{t_{sa}}_i$. For example, if $F^{t_{sa}}_i$ is a feature map extracted from a Deep Neural Network (DNN), an average pooling operator followed by an activation function can be effectively adopted for $A^T_i$.

$$A^T_i = \sigma(A^i_t(F^{t_{sa}}))$$

where $\sigma(\cdot)$ denotes an activation function converting the value range to $[0, 1]$. There are two properties of $A^T_i$. Firstly, a region with higher value of $A^T_i$ is more sensitive to age factor compared to the others. Secondly, according to the depth of $A^T_i$ in the embedding process, different level of attentions can be extracted. Fig. 3 illustrates different attention level of ResNet-18 structure trained for age estimation task. The design of $A^T_i$ is shown in Fig. 2(b) where three operations are adopted including Average Pooling, Sigmoid activation and a dropout layer to enhance the discriminative power for $T^A$. Interestingly, the attention mask of the first sub-function (i.e. ResNet unit) gives a coarse attention to the whole facial region, while the last sub-function pays more attention to specific age-sensitive facial regions.

**Age-invariant Attentive Knowledge.** Although the age-sensitive attentive knowledge can give some hints to the student $S$ to deal with aging factor, this knowledge cannot be directly distilled to $S$. In fact, the goal of $S$ is to be robust against age changing. Therefore, a natural way for $S$ to be beneficial from $A^T_i$ is to pay attention to the “inversion” of $A^T_i$. In other words, we can “flip” the attention of $S$ to the regions that give little contribution to age estimator process, and, therefore, less sensitive to aging changes. Since all values of $A^T_i$ are within the range of $[0, 1]$, an inverse flipping operator can be defined as $1 - A^T_i$. Normally, this operator can give an initial estimation of potential candidates for the age-invariant knowledge. However, the output of this flipping operator may still include other unrelated-regions such as the background outside the face. Interestingly, as illustrated in Fig. 3 although the attention map at a coarsest level of $A^T_i$ provides very low-level attention with more focus on face regions while
disregarding the ones outside the face. Therefore, the age-invariant attentive knowledge for $S$ can be effectively extracted by incorporating this knowledge to the inverse flipping of $\hat{A}_i^T$.

$$\hat{A}_i^T = D_i(A_i^T) \odot (1 - A_i^T), \quad i > 1$$

(4)

where $\odot$ represents the Hadamard product; and $D_i(\cdot)$ denotes a down-sampling operator to match the dimensions between $D_i(A_i^T)$ and $A_i^T$. The last column of Fig. 3 illustrates the age-invariant attention map obtained by $\hat{A}_i^T$ extracted from ResNet structure. Interestingly, the age-invariant attention is mainly distributed around the eyes of the faces. This is consistent with the finding from [16]. However, different from that work, rather than manually pre-defining the periocular region, the design of $\hat{A}_i^T$ can help to adaptively extract them from the input. Moreover, this design becomes more robust and consistent against poses.

**Age-invariant Attentive Distillation.** The knowledge from $\hat{A}_i^T$ is now can be effectively distilled to $S$ by

$$L_{ATT}(S, T^A) = \sum_{i=1}^{C} ||G_i^{s}(\hat{A}_i^T) - G_i^{s}(A_i^S)||_2^2$$

(5)

where $G_i^{s}$ and $G_i^{a}$ are the transformation functions matching the spatial dimensions of $\hat{A}_i^T$ and $A_i^S$. Generally, we can choose the corresponding of $\hat{A}_i^T$ and $A_i^S$ in the structure of $T^A$ and $S$ and choose the identity transformation for $G_i^{s}$ and $G_i^{a}$ to prevent missing information during distillation. During distillation process, to further enhance the attention flow through different levels during the embedding process of $S$, the learned attention mask is also incorporated back to each feature $F^s_i$ by $F^s_i = \hat{A}_i^S \odot F^s_i$ where $\odot$ denotes the spatial multiplication operator.

**B. Feature Direction Knowledge from Teacher**

As in Table I, most prior distillation frameworks are introduced in the closed-set classification problem, i.e. object classification or semantic segmentation with predefined classes. With the assumption about the fixed (and small) number of classes, traditional metrics can be efficiently adopted for the distillation process. For example, given the teacher $T^R$, $\ell_2$-norm distance is usually applied to measure the similarity between $S$ and $T^R$, i.e. $d(G_i^r(F^s_i), G_i^r(F^s_t)) = ||G_i^r(F^s_i) - G_i^r(F^s_t)||_2^2$. Since the capacity of $S$ is limited, employing this constraint as a regularization to each $F^s_i$ can lead to the over-regularized issue. Another metric is to adopt the class probabilities predicted from $T^R$ as the soft target distribution for the student $S$. However, this metric is efficient only when the object classes are fixed in both training and testing phases. Otherwise, the knowledge to convert embedded features to class probabilities cannot be reused during testing stage and, therefore, the distilled knowledge is partially ignored.

In open-set problems, since classes are not predefined beforehand, the sample distributions of each class and the margin between classes become more valuable knowledge. In other words, the angular differences between samples and how the samples distributed in the teacher’s hypersphere are more beneficial to the student. Therefore, we propose to use the angular information as the main knowledge to be distilled. By this way, rather than enforcing the student to follow the exact outputs of the teacher (as in case of $\ell_2$ distance), we can relax the constraint so that the embedded features extracted by the student only need to have similar direction as those extracted by the teacher. Generally, with “softer” distillation constraint, the student is able to adaptively interpret the teacher’s information and learns the solution process more efficiently.

**Softmax Loss Revisit.** As one of the most widely used losses for classification problem, Softmax loss of each input image is formulated as follows.

$$L_{SM} = -\log e^{W_y \cdot F^s_t} \sum_c e^{W_c \cdot F^s_c}$$

$$= -\log \frac{e^{W_y \cdot F^s_t}}{\sum_{c=1}^{C} e^{W_c \cdot F^s_c} \cdot \cos \theta_c}$$

(6)

where $y$ is the index of the correct class of the input image and $C$ denotes the number of classes. Notice that the bias term is fixed to 0 for simplicity. By adopting the $\ell_2$-norm normalisation to both feature $F^s_i$ and weight $W_c$, the angle between them becomes the only classification criteria. If each weight vector $W_c$ is regarded as the representative of class $c$, minimizing the loss means that the samples of each class are
required to be distributed around that class’ representative with the minimal angular difference. This is also true during testing process where the angle between the direction of extracted features from input image and the representative of each class (i.e. classification problem with predefined classes) or extracted features of other sample (i.e. verification problem) are used for deciding whether they belong to the same class. In this respect, the magnitude of the feature $F^s_i$ becomes less important than its direction. Therefore, rather than considering both magnitude and direction of $F^s_i$ for a distillation process, knowledge about the direction is enough for the student to achieve similar distribution to the teacher’s hypersphere. Moreover, this knowledge can be also efficiently reused to compare samples of object classes other than the ones in training.

**Angular Distillation Knowledge.** We propose to use the direction of the teacher feature $F^n_t$ as the distilled knowledge and define an angular distillation loss as follows.

$$L_n(S, T^R) = \left\| 1 - \frac{G^n_t(F^n_t)}{G^n_t(F^n_t)} * \frac{G^n_s(F^n_s)}{G^n_s(F^n_s)} \right\|_2^2$$

(7)

With this form of distillation, as long as $F^n_s$ and $F^n_t$ have similar direction, they can be freely distributed on different hyperspheres with various radius in latent space. This produces a degree of freedom for $S$ to interpret its teacher’s knowledge during learning process. Incorporating this distillation loss to Eqn. (6), the objective function becomes.

$$L = L_{SM} + \lambda_n L_n(S, T^R)$$

(8)

The first term corresponds to the traditional classification loss whereas the second term guides the student to learn from the teacher’s hypersphere. Notice that, this distillation loss can also act as a support to any other loss functions. To prevent missing information during distillation, we choose identity transformation for $T^R$, while $G^n_s(F^n_s)$ is chosen as a mapping function such that the dimension of $F^n_s$ is increased to match the dimension of $F^n_t$, i.e. $1 \times 1$ convolution operator. By this way, no information is missing during feature transformation and, therefore, $S$ can take full advantages of all knowledge from $T$. Geometric Interpretation of the angular distillation knowledge is illustrated in Fig. 4 by considering the binary classification of two classes with the representatives $W_1$ and $W_2$. With higher capacity, the teacher can provide better decision margin between the two classes, while the self-studied student (i.e. using only softmax loss function) can only give small decision margin. When the $L_n(S, T^R)$ is incorporated (i.e. guided student), the classification margin between class 1 and class 2 is further enhanced by following the feature directions of its teacher and produces better decision boundaries. Furthermore, one can easily see that even when the student is not able to produce exact features as its teacher, it can easily mimic the teacher’s feature directions and be beneficial from the teacher’s hypersphere.

**Intermediate Angular Distillation Knowledge.** Generally, if the input to $S$ is interpreted as the question and the distribution of its embedded features is its answer, the generated features at the middle stage, i.e. $F^n_s$, can be viewed as the intermediate understanding or interpretation of the student about the solution process. Then to help the student efficiently “understand” the development of the solution, the teacher should illustrate to the student “how the good features look like” and “whether the current features of the student is good enough to get the solution in later steps”. Then, the teacher can supervise and efficiently correct the student from the beginning and, therefore, leading to more efficient learning process of the student. Inspired by this motivation, we proposed to validate the quality of $F^n_s$ based on its angular difference between the embedding produced by $F^n_t$ and $F^n_{tr}$ using the same teacher’s interpretation toward the last stages. Particularly, given the intermediate feature $F^n_s$, it is firstly transformed by $H^n_t$ to match the dimension of $F^n_{tr}$. Then both $F^n_s$ and $F^n_{tr}$ are analyzed by the teacher $T^R$, i.e. $T^R_i = [T^R_{i+1} \circ \cdots \circ T^R_n]$, for the final embedding features. Finally, their similarity in the hypersphere is used to validate the knowledge that $F^n_s$ embeds.

$$L_i(S, T^R) = d(\hat{T}^R_i(F^n_{tr}), \left[ H^n_t \circ \hat{T}^R_i \right](F^n_s))$$

$$= \left\| 1 - \hat{T}^R_i(F^n_{tr}) * \frac{H^n_t \circ \hat{T}^R_i(F^n_s)}{H^n_t \circ \hat{T}^R_i(F^n_s)} \right\|_2^2$$

(9)

The intuition behind this distillation loss is to validate whether $F^n_s$ contains enough useful information to make the similar decision as its teacher in the later steps by borrowing the
teacher power to solve the solution given the student input at \(i\)-th stage, i.e., \(F_s^i\). In case the teacher can still get similar solution using that input, then the student’s understanding until that stage is acceptable. Otherwise, the student is required to be re-corrected. Fig. 5 illustrates the distillation for intermediate knowledge.

C. Attentive Angular Distillation Network

Fig. 2 illustrates our proposed approach to distill both age-invariant attentive and angular distillation knowledge. ResNet-styled CNN with four ResNet blocks which are adopted for both teacher and student ones. The whole network can be considered as the mapping functions whereas each ResNet block corresponds to each sub-function. It learns a strong but efficient student network by distilling the knowledge to all four blocks. Given a dataset \(D = \{I_j, y_j\}_{j=1}^{N}\) consisting of \(N\) images \(I_j\) and their corresponding labels \(y_j\). The overall learning objective is as,

\[
L = \frac{1}{N} \sum_j \left[ L_{SM} + \lambda^A L^{Att} + \sum_i \lambda_i L_i(S, T^R) \right] 
\]

(10)

where \(\lambda_i\) and \(\lambda^A\) denote the hyper-parameters controlling the balance between the distilled knowledge to be transferred at different ResNet blocks. Moreover, the identity transformation function is used for all functions \(G^j_t\) while \(1 \times 1\) convolution followed by a batch normalization layer is adopted for \(G^j_s\) to match the dimension of the corresponding teacher’s features.

IV. EXPERIMENTAL RESULTS

This work is evaluated on the standard AiFR datasets and compared against the state-of-the-art methods. Unlike prior AiFR works, the proposed approach is also evaluated on the standard large-scale FR benchmarks and compared against recent light-weight FR methods. In addition, we also present a new longitudinal face aging (LogiFace) database for further studies in face-related problems in future.

A. Longitudinal Face Aging (LogiFace) Database

LogiFace database is collected from various resources. Celebrity face images were collected in a wide range of ages from 1 to 99 with both frontal and profile face images. Of the annotation of the dataset, we determined the age of person based on the captured time of images or videos. The photos were captured as color images with a size of \(400 \times 500\) pixels in a PNG format. The database has 12,656 full images of 369 subjects with the average 34 face images per subject. Comparing two of the common public longitudinal face databases FG-NET [25] and MORPH [53], LogiFace is unique in that it contains more longitudinal subject sequences which requires to capture face images of a subject for a long period. Fig. 6 illustrates examples of our LogiFace database.

B. Implementation Details

Databases. Our training data includes MS-Celeb-1M [22] cleaned by [54] with 5.8M photos from 85K identities for FR learning and IMDB-WIKI [55] for Age Estimation learning. We use MS-Celeb-1M to train FR teacher \(T^R\) and IMDB-WIKI to train age estimation teacher \(T^A\). Then MS-Celeb-1M is used to train the student \(S\) with the supports of both \(T^R\) and \(T^A\). For validation, both small-scale and large-scale protocols on AiFR and FR are adopted. In particular, with small-scale protocols, we conduct the experiments on public AiFR datasets including AgeDB [27], FG-NET [56], and our collected LogiFace. While the first two protocols follow the set up of 10-fold validation with positive and negative matching pairs across ages, the latter adopts the leave-one-out (LOO) validation as in [19]. For large-scale benchmark, we validate our proposed AAD approach on the challenging Megaface Protocol 1 on FG-NET set [23] against million-scale of distractors. Furthermore, in order to further evaluate the efficiency and robustness of AAD approach, the performance on standard FR benchmarks including LFW [57], Megaface with FaceScrub Set [23], IJB-B [28], and IJB-C [26] is also reported.
TABLE II
VERIFICATION PERFORMANCE (%) ON FR AND AIFR DATASETS, I.E. LFW, CACD-VS, AGE DB, FG-NET (LOO), AND FG-NET (MF1).

| Backbone | # of params | Ratio | Model Type | LFW | LogiFace | AgeDB | FG-NET (LOO) | FG-NET (MF1) |
|----------|-------------|-------|------------|-----|----------|-------|--------------|--------------|
| ResNet90 [48] | 63.67M | 100% | Teacher | 99.82% | 80.11% | 98.37% | 96.31% | 66.30% |
| MobileNetV1 (MV1) | 3.53M | 5.54% | Self-Studied Student-1 (ℓ2 loss) | 99.60% | 77.12% | 96.83% | 93.51% | 54.66% |
| MobileNetV2 (MV2) | 2.15M | 3.38% | Self-Studied Student-1 (ℓ2 loss) | 99.42% | 76.28% | 95.28% | 92.42% | 49.14% |
| MobileFacenet (MFN) | 1.2M | 1.88% | Self-Studied Student-1 (ℓ2 loss) | 99.45% | 75.49% | 96.17% | 92.72% | 49.84% |
| MobileFacenet-R (MFNR) | 3.73M | 5.86% | Self-Studied Student-1 (ℓ2 loss) | 99.60% | 76.91% | 96.90% | 93.01% | 52.41% |

TABLE III
COMPARISON WITH OTHER METHODS ON AIFR BENCHMARKS.

| Method | Structure Size | FG-NET (LOO) | FG-NET (MF1) |
|--------|---------------|--------------|--------------|
| HFA [14] | – | 69.00% | – |
| MEFA [15] | – | 76.20% | – |
| CAN [21] | – | 86.50% | – |
| LF-CNNs [33] | Large | 88.10% | – |
| A-Softmax [52] | Large | 46.77% | – |
| OE-CNNs [20] | Large | 52.67% | – |
| DAL [19] | Large | 94.50% | 57.92% |
| MV1-AAD | Small | 93.71% | 57.20% |
| MV2-AAD | Small | 93.61% | 54.23% |
| MFN-AAD | Small | 93.11% | 53.46% |
| MFNR-AAD | Small | 95.11% | 60.11% |

TABLE IV
VERIFICATION PERFORMANCE (%) ON LFW.

| Method | TrainingData | Structure Size | Accuracy |
|--------|--------------|----------------|----------|
| Sphereface [58] | 0.5M | Large | 99.42% |
| SphereFace+ [59] | 0.5M | Large | 99.47% |
| Deep-ID2+ [60] | 0.3M | Large | 99.47% |
| Marginal Loss [61] | 4M | Large | 99.48% |
| RangeLoss [62] | 5M | Large | 99.52% |
| FaceNet [63] | 200M | Large | 99.63% |
| CosFace [64] | 5M | Large | 99.73% |
| ArcFace [54] | 5.8M | Large | 99.83% |
| MV1-AAD | 5.8M | Small | 99.63% |
| MV2-AAD | 5.8M | Small | 99.63% |
| MFN-AAD | 5.8M | Small | 99.60% |
| MFNR-AAD | 5.8M | Small | 99.77% |

Model Configurations. In the training stage, the batch size is set to 512. The learning rate starts from 0.1 and the momentum is 0.9. All the models are trained in MXNET environment with a machine of Core i7-6850K @3.6GHz CPU, 64.00 GB RAM with four P6000 GPUs. The λi is experimentally set to 1 in case of Angular Distillation Loss while this parameter is set to 0.001 as the case of ℓ2 loss due to the large value of the loss with large feature map. For the intermediate layers, \( \lambda_i = \frac{\lambda_{i+1}}{2} \).

C. Evaluation Results

AIFR Protocols. We validate the efficiency of our AAD framework with four light-weight backbones on different protocols including LFW, LogiFace (LOO), AgeDB, FG-NET (LOO) and FG-NET (MF1). The ResNet-90 trained on MS-Celeb-1M acts as the teacher network. Then, for each light-weight backbone, four cases are considered: (1) Self-studied student trained without the help from teacher; (2) Student-1 trained using the objective function as Eqn. (10) but only ℓ2 function is adopted for distillation loss; and our proposed framework with (3) Angular Distillation (AD) and (4) Attentive Angular Distillation (AAD) losses. Table II illustrates the performance of the teacher network together with its students. Rank-1 accuracy is reported for LOO validations. Due to the limited-capacity of the light-weight backbones, in all four cases, the self-studied networks leave the performance gaps of 0.22%, 0.40%, 3.14% – 4.62%, 1.47% – 3.09%, and 2.80% – 3.89% with their teacher on LFW, LogiFace, AgeDB, and FG-NET (LOO) respectively. The guided students using ℓ2 loss can slightly improve the accuracy. However, we notice that the training process with ℓ2 loss is unstable. Meanwhile, our proposed framework with AD loss efficiently distills the knowledge from the teacher to its student with the best performance gains that are significantly reduced to only 0.05%, 2.30%, 0.74%, and 2.10% on the four benchmarks, respectively. Moreover, by adopting AAD loss, although the accuracy

Data Preprocessing. All faces are detected using MTCNN [66] and aligned to a predefined template using similarity transformation. They are cropped to the size of 112 × 112.

Network Architectures. In all experiments, ResNet-90 [48] is used as the teacher network, while different light-weight networks, i.e. MobileNetV1 [49], MobileNetV2 [50], MobileFaceNet [51]. A modified version of MobileFacenet, namely MobileFacenet-R, is also adopted for the student network. This modified version is similar to MobileFacenet except the feature size of each ResNet-block is equal to the size of its corresponding features in the teacher network.
on LFW keeps comparable to AD ones, the performance on aging benchmarks are reduced to only 0.07%, 1.91%, 0.64%, and 1.20% on these benchmarks. On the MegaFace benchmark with FG-NET (MF1) probe set, compared to the self-studied students, the ones with AD loss improve by 1.42% to 4.5% according to the capacity of the students. Then, by adopting AAD losses, these improvements are made further to 1.72% - 5.09%. The comparisons with different methods on FG-NET (LOO), FG-NET (MF1), and LFW are also reported in Tables III and IV. These results emphasize the advantages of our AAD by outperforming DAL [19] even when the light-weight structure MFNR is adopted.

**Megaface Protocol.** We further evaluate our AAD approach on the challenging Megaface benchmark against millions of distractors on both FaceScrub and FG-NET sets. The comparison in terms of the Rank-1 identification rates between our AAD and other models is presented in Table V. The face recognition results show the advantages of our AAD with consistent improvements provided to the four light-weight student networks. Particularly, with FaceScrub probe set, the performance gains for the MV1, MV2, MFN, and MFNR are 2.23%, 3.64%, 2.57%, and 1.9%, respectively. Moreover, the MFNR-AAD achieves competitive accuracy (i.e. 95.64%) with other large-scale networks and reduces the gap with ArcFace [54] to only 1.06%.

**IJB-B and IJB-C Protocols.** The comparisons against other recent methods on IJB-B and IJB-C benchmarks are also illustrated in Table VI. Similar to the Megaface protocols, our AAD is able to boost the performance of the light-weight backbone significantly and reduce the performance gap to the large-scale backbone to only 0.019 on IJB-B and 0.016 on IJB-C. These results have further emphasized the advantages of the proposed AAD for model distillation.

V. CONCLUSIONS

This paper presents a novel Attentive Angular Distillation paradigm for age-invariant open-set face recognition. By adopting the proposed Age-invariant Attentive and Angular Distillation Losses for the distillation of feature embedding process, the student network can absorb the knowledge of the teacher’s hypersphere and age-invariant attention in an relaxing and efficient manners. These learned knowledge can be flexibly adopted even when the testing classes are different from the training ones. Evaluation in both small- and large-scale protocols showed the advantages of the proposed AAD framework.

REFERENCES

[1] G. E. Hinton, O. Vinyals, and J. Dean, “Distilling the knowledge in a neural network,” CoRR, vol. abs/1503.02531, 2015.
[2] A. Romero, N. Ballas, S. E. Kahou, A. Chassang, C. Gatta, and Y. Bengio, “Finites: Hints for thin deep nets,” in 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings, 2015.
[3] S. Zagoruyko and N. Komodakis, “Paying more attention to attention transfer,” in 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings, 2017.
[4] J. Yin, D. Joo, J. Bae, and J. Kim, “A gift from knowledge distillation: Fast optimization, network minimization and transfer learning,” in CVPR, July 2017.
[5] S. Srinivas and F. Fleuret, “Knowledge transfer with jacobian matching,” in ICML, vol. 80. PMLR, 2018, pp. 4730–4738.
[6] J. Kim, S. Park, and N. Kwak, “Paraphrasing complex network: Network compression via factor transfer,” in NeurIPS, 2018, pp. 2765–2774.
[7] B. Heo, M. Lee, S. Yun, and J. Y. Choi, “Knowledge transfer via distillation of activation boundaries formed by hidden neurons,” CoRR, vol. abs/1811.03233, 2018.
[8] Y. Wang, C. Xu, C. Xu, and D. Tao, “Adversarial learning of portable student networks,” in Thirty-Second AAAI Conference on Artificial Intelligence, 2018.
[9] S. H. B. S. C. X. D. T. Tianyu Guo, Chang Xu, “Robust student network learning,” in CVPR, 2018.
[10] F. Xu, K. Liu, and M. Savvides, “Spartans: Single-sample pericellular-based alignment-robust recognition technique applied to non-frontal scenarios,” TIP, vol. 24, pp. 4780–4795, 2015.
[11] K. Liu, “Computer approaches for face aging problems,” in CAI. Ottawa, Canada, 2010.
[12] K. Liu, K. R. Jr., T. D. Bui, and C. Y. Suen, “The familial face database: A longitudinal study of family-based growth and development on face recognition,” in Robust Biometrics: Understanding Science & Technology (ROBUST). IEEE, 2008.
[13] D. Chen, X. Cao, F. Wen, and J. Sun, “Blessing of dimensionality: High-dimensional feature and its efficient compression for face verification,” in CVPR, June 2013, pp. 3025–3032.
[14] D. Gong, Z. Li, D. Lin, J. Liu, and X. Tang, “Hidden factor analysis for age invariant face recognition,” in 2013 IEEE International Conference on Computer Vision, Dec 2013, pp. 2872–2879.
[15] D. Gong, Z. Li, Dacheng Tao, J. Liu, and Xuelong Li, “A maximum entropy feature descriptor for age invariant face recognition,” in CVPR, June 2015, pp. 5289–5297.
[16] F. Juefei-Xu, K. Liu, M. Savvides, T. Bui, and C. Suen, “Investigating age invariant face recognition based on pericellular biometrics,” International Joint Conference on Biometrics, 10 2011.
C. Whitelam, E. Taborsky, A. Blanton, B. Maze, J. Adams, T. Miller, S. Moschoglou, A. Papaioannou, C. Sagonas, J. Deng, I. Kotsia, and S. Sengupta, J.-C. Chen, C. Castillo, V. M. Patel, R. Chellappa, and T. Zheng, W. Deng, and J. Hu, “Cross-age LFW: A database for age-invariant face recognition,” in CVPR, 2019.

Y. Wang, D. Gong, Z. Zhou, X. Ji, H. Wang, Z. Li, W. Liu, and T. Zhang, “Orthogonal deep features decomposition for age-invariant face recognition,” in Computer Vision – ECCV 2018, V. Ferrari, M. Hebert, C. Sminchisescu, and Y. Weiss, Eds. Cham: Springer International Publishing, 2018, pp. 764–779.

C. Xu, Q. Liu, and M. Ye, “Age invariant face recognition and retrieval by coupled auto-encoder networks,” Neurocomputing, vol. 222, pp. 62 – 71, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0925231216317299.

Y. Guo, L. Zhang, Y. Hu, X. He, and J. Gao, “Ms-celeb-1m: A dataset and benchmark for large-scale face recognition,” in European Conference on Computer Vision. Springer, 2016, pp. 87–102.

I. Kemelmacher-Shlizerman, S. M. Seitz, D. Miller, and E. Brossard, “The megaface benchmark: 1 million faces for recognition at scale,” in CVPR, 2016, pp. 4873–4882.

B.-C. Chen, C.-S. Chen, and W. H. Hsu, “Cross-age reference coding for age-invariant face recognition and retrieval,” in Proceedings of the European Conference on Computer Vision (ECCV), 2014.

Y. Fu, T. M. Hospedales, T. Xiang, Y. Yao, and S. Gong, “Interestness prediction by robust learning to rank,” in ECCV, 2014.

B. Maze, J. Adams, J. A. Duncan, N. Kalka, T. Miller, C. Otto, A. K. Jain, W. T. Niggel, J. Anderson, J. Cheney et al., “Larpa janus benchmark-c: Face dataset and protocol,” in 2018 International Conference on Pattern Recognition (ICPR), 2018, pp. 158–165.

S. Moschoglou, A. Papaioannou, C. Sagonas, J. Deng, I. Kotsia, and S. Zafeiriou, “Agedb: the first manually collected, in-the-wild age database,” in CVPRW, 2017, pp. 51–59.

C. Whitelam, E. Taborsky, A. Blanton, B. Maze, J. Adams, T. Miller, N. Kalka, A. K. Jain, J. A. Duncan, K. Allen et al., “Larpa janus benchmark-b face dataset,” in CVPRW, 2017, pp. 90–98.

T. Zheng, W. Deng, and J. Hu, “Cross-age LFW: A database for studying cross-age face recognition in unconstrained environments,” CoRR, vol. abs/1708.08197, 2017. [Online]. Available: http://arxiv.org/abs/1708.08197.

S. Sengupta, J.-C. Chen, C. Castillo, V. M. Patel, R. Challappa, and D. W. Jacobs, “Frontal to profile face verification in the wild,” in WACV. IEEE, 2016, pp. 1–9.

C. N. Duong, K. Luu, K. G. Quach, and N. Le, “Shrinkteanet: Million-scale lightweight face recognition via shrinking teacher-student networks.” arXiv preprint arXiv:1905.10620, 2019.

C. N. Duong, K. G. Quach, I. Jalata, N. Le, and K. Luu, “Mobiface: A lightweight deep learning face recognition on mobile devices,” BTAS, 2019.

Y. Wen, Z. Li, and Y. Qiao, “Latent factor guided convolutional neural networks for age-invariant face recognition,” in CVPR, 2016, pp. 4893–4901.

C. N. Duong, K. G. Quach, K. Luu, N. Le, and M. Savvides, “Temporal non-volume preserving approach to facial age-progression and age-invariant face recognition,” in ICCV, Oct 2017.

C. N. Duong, K. Luu, K. G. Quach, N. Nguyen, E. Patterson, T. D. Bui, and N. Le, “Automatic face aging via deep reinforcement learning,” in CVPR, 2019, pp. 10013–10022.

C. Chen, W. Yang, Y. Wang, K. Ricanek, and K. Luu, “Facial feature fusion and model selection for age estimation,” in FG. IEEE, 2011, pp. 1–7.

K. Luu, T. D. Bui, K. R. Jr., and C. Y. Suen, “Age estimation using activity appearance,” in ISCV, pp. 1028–1037, Sep 2011.

K. Luu, T. D. Bui, K. R. Jr., and C. Y. Suen, “Age estimation using activity appearance,” in ISCV, pp. 1028–1037, Sep 2011.

S. Mirzadeh, M. Farajtabar, A. Li, and H. Ghaseimzadeh, “Improved knowledge distillation via teacher assistant: Bridging the gap between student and teacher,” CoRR, vol. abs/1902.03393, 2019.