DISTILLING FACIAL KNOWLEDGE WITH TEACHER-TASKS:
SEMANTIC-SEGMENTATION-FEATURES FOR POSE-INVARIANT FACE-RECOGNITION

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ABSTRACT

This paper demonstrates a novel approach to improve face-recognition pose-invariance using semantic-segmentation features. The proposed Seg-Distilled-ID network jointly learns identification and semantic-segmentation tasks, where the segmentation task is then “distilled” (MobileNet encoder). Performance is benchmarked against three state-of-the-art encoders on a publicly available data-set emphasizing head-pose variations. Experimental evaluations show the Seg-Distilled-ID network shows notable robustness benefits, achieving 99.9% test-accuracy in comparison to 81.6% on ResNet-101, 96.1% on VGG-19 and 96.3% on InceptionV3. This is achieved using approximately one-tenth of the top encoder’s inference parameters. These results demonstrate distilling semantic-segmentation features can efficiently address face-recognition pose-invariance.

Index Terms— Face-Recognition, Head-Pose, Multi-Task-Learning, Knowledge-Distillation

1. INTRODUCTION

Face-recognition (FR) is becoming the go-to authentication technology for access control and verification applications. Its popularity starts with evolution of smart phones, where over 100 million devices offer it as seamless-unlock method [1]. This has led other industries to follow suit, where commercial real-estate [2], aviation [3] and banking [4] now use FR as a means to differentiate customer experience. This is made possible by advances in deep-learning [5]; state-of-the-art models can now discern 1 cooperative face from over 50,000 [6]. Having robust tolerance to pose-variations, however, is still a challenge [7].

Pose-variations are facial rotations over yaw and pitch. These change the relative-position of key-points (e.g., nose, eyes) and introduce variance within identity classes. As such, FR algorithms can struggle to discern the same person rotating from different people [7]. In particular when applying stringent industry false-acceptance-rate thresholds [6], variations in pose often result in false-rejections [7].

Current state-of-the-art methods rely on alignment techniques and/or sophisticated loss-functions to address pose-variability. Through alignment pre-processing, algorithms can project a cooperative-face for identification [8]. Alternatively, contrastive loss-functions (such as triplet) implicitly address pose-variations through relative class-distance [5]. While notable advances, even best-in-class algorithms struggle to achieve 100% accuracy on competition data-sets [9].

This paper presents the Seg-Distilled-ID network. This is a new approach to knowledge-distillation, using a teacher-task in lieu of a teacher-network. The Seg-Distilled-ID network is first jointly trained on both identification and (teacher) semantic-segmentation tasks, where the teacher-task is then removed. This “distills” the semantic-structures as context for precise identification (see Fig. 1). Recognition accuracy is benchmarked against three state-of-the-art encoders on the Mut1ny commercial face-segmentation data-set [10] (11,830 images selected from 67 subjects, varied over pose and lighting). The proposed Seg-Distilled-ID network achieves 99.9% test-accuracy, compared to 81.6% on ResNet-101 [11], 96.1% on VGG-19 [12] and 96.3% on InceptionV3 [13]. This is achieved using only 2.4M inference parameters (approximately one-tenth of the top encoders). These results demonstrate distilling semantic-segmentation features can efficiently address face-recognition pose-invariance.

In summary, this paper makes the following contributions:

• Novel knowledge-distillation method via teacher-tasks.
• Best-in-class ID accuracy (99.9%, Mut1ny faces [10]).
• Significant parameter efficiency versus top encoders.

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2. RELATED WORKS

Face-recognition (FR) research starts in the 1970s as a template-matching problem. This is pioneered by the discovery that statistical-distributions (e.g., Eigenfaces [14]) are generally robust. This is expanded upon by using hand-crafted features to describe distinguishable features [15]. These features, however, are insufficient at large-scales. This ultimately transitions to deep-learning (DL) solutions (starting with DeepFace [16]). Today, state-of-the-art DL networks emphasize a combination pose-alignment pre-processing [8] (which may include 3-D projection [17, 18]) and contrastive loss-functions [5].

Despite all these advances, pose-variations are still a challenge [7]. To address this, a new trend is to apply multi-task-learning (MTL) for sharing context. This is first exemplified by Ranjan et al, who combine landmarks and pose tasks on a face-detection network (HyperFace) to improve reliability [19]. Others have now recently applied this approach to identification. Yin and Xiaoming have a pose estimation task connected to the identification features [20]. Wang et al alternatively use semantic descriptors of sub-structures: size of eyes, nose and cheeks [21]. Both approaches show consistent (small) improvements on FR competition data-sets.

This research differentiates on these findings by using a knowledge-distillation approach with a precise-descriptor: semantic-segmentation. The aforementioned approaches share common features with the identification task. In this case, the network is jointly trained on facial-structure with identification, then “distills” the teacher-task. The “distilled” semantic-features enable the encoder to generate precise features, enabling efficient pose-invariance recognition.

3. METHODOLOGY

This research proposes a novel application of Multi-Task-Learning (MTL) to improve face-recognition pose-robustness. Facial semantic-segmentation is “distilled” by using a “teacher-task.” By encoding relative facial-structure, the loss function can better discern *inter* versus *intra* class variations.

3.1. Seg-Distilled-ID Network

Fig. 2 shows how the Seg-Distilled-ID network starts with identification and segmentation tasks. The segmentation-task functions as a teacher, helping the ID-task better converge towards optimal weights. Once training is complete the teacher-task is removed (note the dashed lines).
The network assumes a U-Net architecture [22]. U-Net is selected both for its applications to biomedical semantic-segmentation [22] and option for efficient MobileNetV2 encoder [23]. A MobileNetV2 backbone [23] encodes features for parallel identification and semantic-segmentation tasks. The identification-task is constructed by applying a global-average pooling layer, followed with a dense, 128-neuron, feature layer (ReLU activation [24]) and a dense, 67-neuron, classification layer (soft-max activation [25]). The segmentation-task is constructed using the Pix2Pix decoding layers [26] (e.g. final segmentation output of 128 by 128).

Both tasks use a categorical-cross-entropy loss, as shown in (1). This better separates out the (log) distance between classes by incorporating probability of the observation, \( o \), belonging to the label-class, \( c \). This probability can be defined as \( p(o, c) \) [25]. A binary label, \( \hat{y} \), indicates whether the prediction matches the correct class. This is done per class \( c \) of \( M \) in an expected-value fashion.

\[
CE = -\sum_{c=1}^{M} \hat{y}_{o,c} \log p(o, c) \tag{1}
\]

Equation (2) shows the joint MTL-loss as a linear combination. Both identification and semantic-segmentation are multi-class-tasks, employing (categorical) cross-entropy loss. The losses are weighted in a 10 to 1 ratio; this is because the segmentation-task is both inherently harder and functions as the “teacher” for “distillation.” This is described in (2), where \( CE \) is the cross-entropy loss function, \( Y \) and \( \hat{Y} \) are the respective task inference and label vectors, and \( \lambda \) is the loss-weight (i.e., 1 and .1 respectively).

\[
Loss = \lambda_{Seg} \cdot CE(Y_{Seg}, \hat{Y}_{Seg}) + \lambda_{ID} \cdot CE(Y_{ID}, \hat{Y}_{ID}) \tag{2}
\]

Once training is complete, the teacher segmentation-task-layers are removed. This significantly reduces the network parameters, from 6.5M to 2.4M, for inference. Fig. 1 shows the final inference structure (see: first-page), where the encoder color change represents the segmentation knowledge-distillation. The purpose of this architecture is to both retain efficiency while demonstrating the dark-knowledge of the segmentation task is sufficient to improve identification.

4. PERFORMANCE EVALUATION

This experiment evaluates the identification accuracy when introducing significant pose-variations. The purpose is to demonstrate the utility of distilling face-segmentation as contextual features. The Seg-Distilled-ID network is validated against identification networks using MobileNetV2 [23] without segmentation-context and three state-of-the-art network encoders.

4.1. Experiment: Pose-Invariant Identification

This experiment evaluates identification performance under high pose-variation. The Mut1ny Face/Head Segmentation (commercial edition) data-set [10] is used, employing 67 synthetic users with 150-250 unique perspectives (pose and background) each (11830 total). Each face is annotated with 14 structure classes: lips, left-eye, right-eye, nose, skin, hair, left-eyebrow, right-eyebrow, left-ear, right-ear, teeth, facial-hair, spectacles and background. These are cropped using the Dlib face detection tool [27]. Model verification-accuracy is measured following Labelled Faces in the Wild procedures [9]. Each person has 90% of their face-perspectives associated for training (8,320) and validation (2,080); test accuracy is evaluated on the remaining 10% (1,430).

Fig. 3 shows some sample images (with segmentation-masks) from the evaluation data-set. While there are only 67 people, it is a very challenging face-recognition data-set. There are differences in pose, accessories, facial-hair and illumination. These significantly increase intra-class variability.
4.2. Benchmark Algorithms

The Seg-Distilled-ID network is benchmarked against three state-of-the-art encoders and MobileNetV2 without teacher-task [23]. Note that this is a comparison of encoder knowledge where inputs and ID-loss-function are kept identical. Furthermore, a comparison of pose-estimation versus semantic-segmentation context is viewed as relevant due to the work of Yin [20]. However, given the Mut1ny data-set does not contain the same pose-annotations, it is not pragmatic to do so. Evaluating input transformation, loss-function and task-sharing approaches are viewed as key next steps.

Each benchmark network follows the same ID task-structure. That is to say an encoder generates the features, where are global-average-pooled, then classified using a 128-neuron dense feature-layer (ReLU activation) [24] and 67-neuron dense ID-classification-layer (soft-max activation) [25]. The following network feature-encoders are used:

1. MobileNetV2 [23]
2. ResNet-101 [11]
3. VGG-19 [12]
4. InceptionV3 [13]

Each network is referred to as the encoder “-ID”. E.g., validation-network 1 is designated “MobileNetV2-ID.” All feature-encoders come pre-trained on ImageNet [28]. Networks are compiled and trained in the same fashion, up to 125 epochs with a validation-loss patience of 20. Due to space constraints, training and validation curves are not shown.

5. EVALUATION RESULTS

Table 1 shows the performance evaluation results. As generally expected, having a stronger encoder correlates with better ID classification. All networks but MobileNetV2-ID train to a validation accuracy of at least 95% (training data not shown for space). This understandable from the encoder architectures. For example, InceptionV3-ID network has a relatively-high parameter-count with factorized-convolutions [13] and trains robustly. Conversely, the MobileNetV2-ID stops early and clearly over-fits due to its efficient design.

| Network          | Parameters | Test Accuracy |
|------------------|------------|---------------|
| MobileNetV2-ID   | 2.4M       | 21.9%         |
| ResNet-101-ID    | 43M        | 81.6%         |
| VGG-19-ID        | 20M        | 96.1%         |
| InceptionV3-ID   | 22M        | 96.3%         |
| **Seg-Distilled-ID** | **2.4M (6.5M +Seg)** | **99.9%** |

This performance disparity exemplifies the benefits of distilling semantic-segmentation features. Despite MobileNetV2-ID over-fitting, the Seg-Distilled-ID has the highest accuracy score evaluated. This is achieved while retaining the MobileNet architecture’s efficiency (approximately one-tenth of the VGG and Inception network parameters). The parenthesis indicates that 2.4M parameters are used for inference and 6.5M are used for jointly training with the teacher-task.

The parameter efficiency is explainable by using the semantic-segmentation knowledge to select optimal features. Top-tier encoders use large parameter-spaces to implicitly infer context, enabling them to perceive information the base MobileNetV2-ID cannot. This methodology instead explicitly provides context through the facial-structure teacher-task. Fig. 3 shows the semantic-segmentation masks; one can infer how the features that encode facial-structure variation across pose enable precise identification across pose. This feature robustness enables the Seg-Distilled-ID to efficiently achieve best-in-class performance.

Note that generalized pose robustness is very much novel. Others demonstrate re-aligning the face in 3-D space can improve identification robustness (such as LDF-Net [17] and GridFace [18]). These methods are effective but degrade as yaw and pitch increase. It is hypothesized the 3-D alignment algorithms synthetically inferring the obscured facial features cascades bias from the projector. The Seg-Distilled-ID avoids this bias by learning facial-structures in a one-shot approach.

6. CONCLUSIONS

This paper presents the Seg-Distilled-ID network to address pose-invariance face-recognition. This is a novel application of knowledge-distillation, where an ID-task is jointly-trained with a “distilled” teacher semantic-segmentation-task. Benchmarking with state-of-the-art encoders ResNet-101 [11], VGG-19 [12] and InceptionV3 [13] shows the proposed Seg-Distilled-ID network achieves best-in-class performance using minimal parameters (MobileNetV2 [23] encoder).

Next steps include larger-scale evaluation with varied context-encoding methods. The Mut1ny data-set [10] has only 67 subjects in the synthetic-face repository at this time; hence, the planned next step is attempt transfer-learning these features onto Labelled Faces in the Wild [9]. To accommodate the increase in ID classes, a comparison of U-Net [22] and DeepLabV3 [29] designs will be done with various task-architectures. Benchmarking will also include face-alignment pre-processing and contrastive loss-functions.

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