Synthesis-Guided Feature Learning for Cross-Spectral Periocular Recognition

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Abstract—A common yet challenging scenario in periocular biometrics is cross-spectral matching - in particular, the matching of visible wavelength against near-infrared (NIR) periocular images. We propose a novel approach to cross-spectral periocular verification that primarily focuses on learning a mapping from visible and NIR periocular images to a shared latent representational subspace, and supports this effort by simultaneously learning intra-spectral image reconstruction. We show the auxiliary image reconstruction task (and in particular the reconstruction of high-level, semantic features) results in learning a more discriminative, domain-invariant subspace compared to the baseline while incurring no additional computational or memory costs at test-time. The proposed Coupled Conditional Generative Adversarial Network (CoGAN) architecture uses paired generator networks (one operating on visible images and the other on NIR) composed of U-Nets with ResNet-18 encoders trained for feature learning via contrastive loss and for intra-spectral image reconstruction with adversarial, pixel-based, and perceptual reconstruction losses. Moreover, the proposed CoGAN model beats the current state-of-art (SotA) in cross-spectral periocular recognition. On the Hong Kong PolyU benchmark dataset, we achieve 98.65% AUC and 5.14% EER compared to the SotA EER of 8.02%. On the Cross-Eyed dataset, we achieve 99.31% AUC and 3.99% EER versus useability. Cross-spectral recognition further relaxes the constraints imposed on input images at the cost of introducing a challenging domain gap between images of different spectral wavelengths. However, this proposition is made more attractive for periocular recognition due to the prevalence of iris recognition systems which typically generate near-infrared (NIR) periocular images, and also to the increased use of masks being worn which partially obscure the face. Examples of periocular images are shown in Fig. 1.

I. INTRODUCTION

Periocular recognition uses the region surrounding the eye to recognize individuals. The periocular region can offer a good trade-off in terms of recognition accuracy versus useability. Cross-spectral recognition further relaxes the constraints imposed on input images at the cost of introducing a challenging domain gap between images of different spectral wavelengths. However, this proposition is made more attractive for periocular recognition due to the prevalence of iris recognition systems which typically generate near-infrared (NIR) periocular images, and also to the increased use of masks being worn which partially obscure the face. Examples of periocular images are shown in Fig. 1.

Two common strategies to address the cross-spectral domain-shift are to 1) map images of either domain to a shared representational subspace [1], [2], [7], [18], or 2) translate images from one domain to the other [8], typically to use an existing uni-modal recognition model. Drawing on elements of both strategies, we propose a novel approach to cross-spectral periocular recognition which utilizes coupled convolutional neural networks (CNN) to perform shared latent subspace learning and feature matching while simultaneously leveraging Conditional Generative Adversarial Networks [4], [12] (cGAN) to guide the learning process.

II. RELATED WORKS

Deep-learning based approaches have been used in a variety of periocular biometric scenarios including intra-spectral recognition [6], [7], [11], [18], bi-modal fusion [18], and cross-spectral recognition [1], [8], [18]. In cross-spectral periocular recognition, near perfect or perfect results have been attained [1], [8], [18] on the Hong Kong PolyU [13] and Cross-Eyed [15] closed world protocols due to the high correlation between the non-class-disjoint train and test data. However, Zanlorensi et al. [18] also achieve state-of-the-art performance on the more challenging class-disjoint open world protocol using coupled ResNet-50 [5] networks trained for feature extraction and matching. Our approach primarily differs in that we enhance the subspace feature learning by simultaneously training for image reconstruction in a multi-task fashion while also using a much smaller ResNet-18 [5] network.

A generative adversarial network (GAN) [4] is composed of a generator network $G(z)$ which generates data given a random input vector $z$, and a discriminator network $D(\cdot)$ which outputs the probability that the input came from the
Fig. 2: The CoGAN architecture composed of coupled ResNet-18 encoders (yellow) embedded within dual U-Net cGANs.

The overall architecture of the proposed Coupled GAN (CoGAN) is primarily composed of two cGANs. One cGAN processes visible-wavelength images while the other processes NIR images. The networks are “coupled” by the joint task of learning a mapping from periocular images to feature representations in a common latent subspace. While our ultimate goal is to learn discriminative and domain-invariant feature encodings for cross-spectral periocular recognition, we propose to simultaneously optimize for a set of auxiliary objectives related to image reconstruction. We hypothesize these secondary reconstruction tasks can help the feature learning process key into important visual features.

Fig. 2 illustrates the CoGAN’s main components. The generators have a U-Net [14] encoder-decoder structure with ResNet-18 [5] encoders (minus the final softmax layer) followed by deconvolutional decoder layers. The discriminators are VGG-like [16] 4-layer CNNs (with filters sizes of 16, 32, 64, and 128, respectively) followed by a fully-connected layer with a single scalar output. The perceptual network is an ImageNet pre-trained VGG16 network. Once the model has been trained, the encoders can operate in isolation from the rest of the CoGAN.

1) Shared Feature Subspace Learning: The ultimate goal of the Coupled GAN is to conduct cross-spectral matching by learning discriminative, domain-invariant features. The contrastive loss [2] term is the portion of the objective function which is most directly related to our ultimate goal. All other losses are auxiliary to the learning process. Minimizing the contrastive loss encourages the features extracted from a pair of genuine images (i.e. instances of the same class) to be similar and the features of imposter pairs (instances of different classes) to be least some margin $m$ apart. Let $X_V = \{x_i^V\}_{i=1}^N$ and $X_I = \{x_i^I\}_{i=1}^N$ be the visible wavelength and near-infrared periocular images, respectively. Let $D_s(x_i^V; x_j^I)$ be the distance measure between the features extracted from a pair of images. Given the feature encodings
we calculate the distance measure as the L2-norm:

\[ D_z(x_i^V; x_i^I) = \left\| z_1(x_i^V) - z_2(x_i^I) \right\|_2. \]  

(2)

Let us define ground-truth labels \( y_{ij} = 0 \) for genuine pairs and \( y_{ij} = 1 \) for imposter pairs. The contrastive loss function is then written as:

\[ L_C(x_i^V; x_i^I; y_{ij}) = (1 - y_{ij}) \frac{1}{2} (D_z(x_i^V, x_i^I))^2 
+ (y_{ij}) \frac{1}{2} (\max(0, m - D_z(x_i^V, x_i^I)))^2, \]  

(3)

\[ L_C^* = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} L_C(x_i^V, x_i^I, y_{ij}), \]  

(4)

where \( L_C^* \) denotes a combined loss computed over both visible and NIR domains.

A. Image Synthesis

Instead of performing cross-spectral image synthesis, we utilize the pair of cGANs to refine the feature learning process via three auxiliary loss terms: adversarial loss, reconstruction loss, and perceptual loss; all of which work in concert with the contrastive loss to help guide the encoders in learning important visual features.

1) Adversarial Loss: Using \( \phi \) for the adversarial loss of a single cGAN, we condition on the input images in order to recreate them. Let \( G_V \) and \( G_I \) be generators operating on visible and IR images, respectively, while \( D_V \) and \( D_I \) are their respective discriminators. The total adversarial loss for the coupled networks is:

\[ L_A^* = \frac{1}{N^2} \left( \sum_{i=1}^{N} L_{cGAN}(G_V, D_V, x_i^V, x_i^V) \right) 
+ \frac{1}{N^2} \left( \sum_{j=1}^{N} L_{cGAN}(G_I, D_I, x_i^I, x_i^I) \right). \]  

(5)

2) Reconstruction Loss: Minimizing the reconstruction loss trains the GAN to recreate low-level, fine-grained features. We use the L2 distance between the pixel values of a given image \( x \) and its synthesized version \( \hat{G}(x) \) as the reconstruction loss. The total reconstruction loss is defined as follows:

\[ L_R(x; G) = \| x - G(x) \|_2^2, \]  

(6)

\[ L_R^* = \frac{1}{N^2} \left( \sum_{i=1}^{N} L_R(x_i^V, G_V) \right) + \frac{1}{N^2} \left( \sum_{j=1}^{N} L_R(x_i^I, G_I) \right). \]  

(7)

3) Perceptual Loss: Given an image \( x \) and its reconstruction, the perceptual loss [10] measures the distance between the high-level features extracted by the \( k \)th layer of a fixed loss network \( \phi \). Let \( \phi_k(\cdot) \) be the \( C_k \times W_k \times H_k \) activations of the \( k \)th network layer for a given input image. The perceptual loss is the L2 distance between the feature representations:

\[ L_P(x; G) = \frac{1}{CWH} \sum_{c=1}^{C_k} \sum_{w=1}^{W_k} \sum_{h=1}^{H_k} \| \phi_k(x) - \phi_k(G(x)) \|_2^2, \]  

(8)

\[ L_P^* = \frac{1}{N^2} \left( \sum_{i=1}^{N} L_P(x_i^V, G_V) \right) + \frac{1}{N^2} \left( \sum_{j=1}^{N} L_P(x_i^I, G_I) \right). \]  

(9)

We use the activations of the last convolutional layer of a pre-trained VGG16 network for \( \phi_k \).

B. Training and Implementation

The overall objective function of the Coupled GAN is the summation of the multi-task losses plus an additional L2 weight decay term:

\[ L = \lambda_C L_C^* + \lambda_A L_A^* + \lambda_R L_R^* + \lambda_P L_P^* + \lambda L_2 L_{L_2}, \]  

(10)

where \( \lambda \) represents the coefficients of the individual loss terms. This function is minimized by Stochastic Gradient Descent via the Adam optimizer.

We set \( \lambda_A = \lambda_R = \lambda_P = 1.0 \). Optimal values for \( \lambda_C \) vary slightly depending on the dataset (see Section V-B). The learning rate and L2 weight decay (\( \lambda_{L2} \)) are fixed at \( 1 \times 10^{-4} \). Training is done for 300 epochs, with every mini-batch composed of 100 NIR-visible image pairs, resized to 256 \( \times \) 256, for a total mini-batch size of 200 images. Each pair has a 50% chance of being either a genuine or imposter pair. A 5-fold cross validation scheme on the training data was employed to tune hyperparameters and determine the number of training epochs. The models were implemented with Pytorch 1.7.0 on machines with 2x Tesla V100 GPUs. The code has been made available at https://github.com/vonclites/cogan.

IV. DATASETS

Our approach is benchmarked on the open world protocols of Hong Kong PolyU [13] and Cross-Eyed [15] datasets following the method used in [18]. Dataset details are provided in Table [I] and example images in Fig. [I]. Following standard practice in periscopic recognition, we consider a subject’s left and right eyes to be unique classes. Verification is conducted using a one-against-all pairwise matching strategy.

The Hong Kong PolyU [13] dataset is composed of simultaneously acquired images in the NIR and visible spectrums. The entire database has 12,540 images with a resolution of 640\( \times \)480. In both visible and thermal spectrums, there are 15 samples of each eye (left and right) from 209 subjects (418 classes). The first 104 subjects plus the left eye of the 105th are assigned to the training set and the rest to testing. The Cross-Eyed [15] dataset has 3,840 images from 120 subjects (240 classes). There are eight samples from each
TABLE I: Open world protocol of the Hong Kong PolyU and Cross-Eyed cross-spectral periocular datasets.

| Dataset       | Train/Test Subjects | Train/Test Classes | Train/Test Images | Gen/Imposter Test Pairs |
|---------------|---------------------|--------------------|-------------------|-------------------------|
| HK PolyU      | 104.5/104.5         | 269/209            | 6,270/6,270       | 21,945/9,781, 200      |
| Cross-Eyed    | 60/60               | 120/120            | 1,920/1,920       | 3,360/913, 920         |

TABLE II: Comparison with State-of-the-Art and baseline.

| Dataset       | Model       | AUC% | EER% | FRR@FAR |
|---------------|-------------|------|------|---------|
|                |             | 1%   | 10%  |         |
| HK PolyU      | ResNet-50   | 96.03| 9.93 | 31.22   | 11.25   |
|               | CoGAN       | 98.65| 5.14 | 12.32   | 3.27    |
|               | Zanlorensi  | -    | 8.02 | -       | -       |
| Cross-Eyed    | ResNet-50   | 95.43| 10.00| 26.43   | 10.04   |
|               | CoGAN       | 99.41| 3.07 | 6.11    | 1.66    |
|               | ResNet-18   | 98.16| 5.85 | 18.6    | 4.36    |
|               | Zanlorensi  | -    | 4.39 | -       | -       |
|               | ResNet-18   | 98.95| 4.15 | 10.19   | 2.62    |
|               | CoGAN       | 99.41| 3.07 | 6.11    | 1.66    |

of the classes for each spectrum. All images are 400x300 resolution and were obtained at a distance of 1.5 meters. The first 60 subjects are assigned to the training set and the remaining 60 to the test set.

Images are rescaled to 256 × 256 with zero mean and unit variance per training data statistics. For data augmentation, training images are zero-padded to 272 × 272 and a 256 × 256 crop is extracted.

V. RESULTS AND DISCUSSION

In this section, we present and discuss the benchmark results of the CoGAN framework along with additional experiments and ablation studies investigating the benefits of our hybrid approach. Once trained, the only components which are utilized for evaluating the CoGAN’s performance are the encoder sub-networks. Performance is evaluated in terms of the Area Under the ROC Curve (AUC) and Equal Error Rate (EER). Also provided is the False Rejection Rate at False Accept Rates of 1% and 10% (FRR@FAR=1%, FRR@FAR=10%).

A. Comparison with State of the Art

At the time of writing, the only recent work which reports results on the open world protocols of the benchmark datasets is, to the best of our knowledge, Zanlorensi et al. [18], who have achieved state-of-the-art performance on the cross-spectral scenario. In Table II, the performance of the proposed CoGAN model is compared with the state-of-the-art and two baselines models. The baseline versions are equivalent to training the CoGAN using only contrastive loss and weight decay. The CoGAN achieves improved EER(%) over the ResNet18 baseline and the larger, coupled ResNet-50 model of [18], which in turn performs better than our ResNet-50 baseline, potentially due to their use of cosine similarity. ResNet-18 can also be seen to outperform ResNet-50, consistent with the intra-spectral periocular recognition results reported in [11].

TABLE III: Feature Dimension Size |z| vs. Contrastive Cost Coefficient λC in terms of AUC(%) of λA, λR, λP set to 1.0.

| Dataset       | |λC| | λA| | λR| | λP| | AUC, % |
|---------------| |   | |   | |   | |   |         |
| HK PolyU      | 1.0| 2.0| 5.0| 10.0| 98.41|
| Cross-Eyed    | 32 | 98.74| 98.85| 98.65| 98.42|
|               | 64 | 98.25| 97.95| 97.87| 97.92|
|               | 128| 98.28| 98.76| 98.89| 98.38|
|               | 256| 98.19| 99.24| 99.31| 99.41|

TABLE IV: The effect of the auxiliary image synthesis tasks (adversarial loss λA, reconstruction loss λR, and perceptual loss λP) on the HK PolyU dataset.

B. Ablation Studies

The following ablation studies serve to further evaluate the performance of the CoGAN and the effect of the auxiliary image synthesis tasks on the end-goal of periocular verification. Table III lists the AUC(%) for various sizes of the feature encoding vectors (z1 and z2) and contrastive cost coefficients (λC). Similar to [18], we also found the optimal feature size to be smaller for the Hong Kong dataset than the Cross-Eyed.

Table IV shows the gradual improvements gained by incorporating the additional loss terms of the GAN. The first row of the table represents a baseline version of the model constrained only by the primary contrastive loss objective. We can see that the largest impact over the baseline is made by a combination of adversarial and perceptual loss. This suggests that by emphasizing the importance of capturing the high-level, global appearance, the CoGAN is better able to guide the learning of discriminative features.

VI. CONCLUSION

We show our novel approach to cross-spectral periocular recognition achieves state-of-the-art results using the proposed CoGAN architecture. Our experiments demonstrate that by introducing auxiliary intra-spectral image reconstruction tasks to support the effort of shared subspace feature learning for cross-spectral periocular recognition, the CoGAN attains higher performance over a baseline version.
of the model. Our work presents the CoGAN architecture as a promising framework for further research in both intra-spectral and cross-spectral periocular recognition, given the compact nature of its ResNet-18 backbone, lack of need for well-aligned image pairs, and potential for cross-spectral synthesis applications. In particular, our investigation reveals that perceptual loss may aid in disentangling domain-specific information from the feature representations used for matching, indicating a potential direction for future work.

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