Deep Domain Adaption for Convolutional Neural Network (CNN) based Iris Segmentation: Solutions and Pitfalls

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Abstract: Addressing the lack of massive amounts of labeled training data, deep domain adaptation has been applied successfully in many applications of machine learning. We investigate the application of deep domain adaptation for CNN based iris segmentation, exploring available solutions and their corresponding strengths and pitfalls, with several major contributions. First, we provide a comprehensive survey of current deep domain adaptation methods according to the properties of data that cause the domains divergence. Second, after selecting credible methods, we evaluate their expedience in terms of iris segmentation performance. Third, we analyze and compare the performance against the state-of-the-art methods under these categories. Forth, potential shortfalls of current methods and several future directions are pointed out and discussed.

Keywords: Deep domain adaptation, iris segmentation, convolutional neural networks.

1 Introduction

Iris recognition has emerged as a rapidly growing field of research in past decades. Iris segmentation is a critical step in the entire iris recognition system. Owing to their superior performance, recently segmentation-oriented CNNs are proposed as a new paradigm for iris segmentation. Basically, the networks are trained on samples of the source data for which ground-truth labels are available. Having available a new target data (whose distribution is different from the source data), for which the ground-truth labels are not available, we aim to apply the trained (on the source data) network on the target data. Because of many factors (*e.g*. illumination, pose, and image quality), there is normally a distribution change or domain shift between the source and the target data (*i.e*. collected from different sensors), causing the CNNs to fail in performing the segmentation in the target data well. Domain adaptation (DA) is a particular case of transfer learning (TL), that addresses this problem utilizing labeled data in the source domain to execute new tasks in a target data domain (for which the target labels are not available). Deep networks can represent high-level abstractions by multiple layers of non-linear transformations. So, they can learn more transferable representations that disentangle the factors of variations underlying the data samples and group features hierarchically in accordance with their relatedness to invariant factors.

In this paper, we are focused on investigating and evaluating deep domain adaptation (DDA) methods for iris segmentation using CNNs. In particular, we present a taxonomy

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of available deep DA methods according to the properties of data that define in how far two domains are different. Analyzing the convolutional neural models and also the mechanisms and approaches used for the adaptation, we select certain plausible methods to be evaluated for adapting domains between different well-known iris databases (as used in our experiments). The performance is evaluated in terms of the resulting iris segmentation output accuracy, and then compared against the most recent methods among these categories, where leverages and drawbacks in each case are analyzed and discussed. At the end, some general pitfalls of current deep DA methods for adapting the domains between different iris data, as well as several future headings will be outlined and discussed.

2 DDA overview and related work

The only work specifically dedicated to the domain adaptation for CNN based iris segmentation is proposed by Jalilian *et al.* [JUK17]. They proposed two (shallow) pixel-level domain adaptations (a linear- and a nonlinear-based method), to transfer the domains of the source iris databases to those of the targets. Both methods require the target data labels to perform the mapping between the domains. However, these labels are not available in real case scenarios, and in fact this is the main objective of using domain adaptation. Domain adaptation in computer vision can be generally split into two main categories based on different domain divergences: Homogeneous DA, where feature space distributions between domains differ (*i.e.* change in illumination, pose), and heterogeneous DA, where dimensions of feature spaces also may differ in the domains (*e.g.* RGB vs. depth data). In the followings we will review different deep techniques proposed in each category briefly.

2.1 Homogeneous discrepancy-based approaches

Class criterion: Uses the class label information as a guide for transferring class knowledge between different domains. Most works in this category use target class label information in a supervised DA framework to preserve the relationships between classes across domains [Tz15]. Alternative techniques such as using pseudo labels, and attribute representation [Ya17] (semi-supervised DA) generally do not deliver promising results as the labels do not generalize well to the target domains (qualitatively or quantitatively).

Statistic criterion: Aligns the statistical distribution shifts, comparing the distributions between two databases using well-known methods like: Maximum Mean Discrepancy (MMD), Correlation Alignment (CORAL), etc. Long *et al.* [Lo15] extended MMD to a deep framework and proposed a Deep Adaptation Network (DAN) that matches the shift in marginal distributions across domains by adding multiple adaptation layers and exploring multiple kernels. The Deep Domain Confusion network (DDC) by Tzeng *et al.* [Tz14] uses two CNNs for source and target domains with shared weights. The domains' difference then is measured by an adaptation layer with the MMD metric. [Zh15] proposed a deep transformation model, in which both the marginal and the conditional distributions are matched based on MMD.

Architecture criterion: Aims at minimizing the distribution discrepancy between domains by adjusting the architectures of deep networks. Rozantsev *et al.* [RSF19] proposed a two-stream CNN, in which the first stream operates on the source data, and the second stream operates on the target data, while they are jointly trained with shared weights. They regularized the weights in an exponential loss function, while they allowed the weights in one stream to undergo a linear transformation:

$$\psi_w(\theta_j{}^s, \theta_j{}^t) = exp(||a_j\theta_j{}^s + b_j - \theta_j{}^s||^2) - 1, \tag{1}$$

where a_j and b_j are scalar parameters, and $\theta_j{}^s$ and $\theta_j{}^t$ denote the parameters of the j^{th} layer of the source and target models, respectively. Li *et al.* [Li16] later used a batch normalization (B) layer to align the distribution for recomputing the mean and standard deviation in the target domain:

$$B(X^t) = \lambda \frac{x - \mu(X^t)}{\varphi(X^t)} + \alpha, \tag{2}$$

where λ and α are parameters learned from the target data and $\mu(X)$ and $\alpha(X)$ are the mean and standard deviation computed independently for each feature channel.

Geometric criterion: Mitigates the domain shift by integrating intermediate subspaces on a geodesic path from the source to the target domains. E.g. Chopra *et al.* [CBG13] proposed a DDA by Interpolating between Domains (DLID). The model generates an intermediate dataset, by which a deep nonlinear feature extractor using the predictive sparse decomposition is trained in an unsupervised manner.

2.2 Homogeneous adversarial-based approaches

Generative models: Estimate generative models via an adversarial process. So called ”GAN” models [Go14] consist of two modules: generative module G that extracts the data distribution and a discriminative module D that distinguishes whether a sample is from G or the training dataset by predicting a binary label. CoGAN [LT16] consists of a pair of GANs, in which one GAN is used for generating the source data and the other for generating the target data. The weights of the first few layers in the generative module and the last few layers in the discriminative module are shared. The core idea of this type of models is generating synthetic target data that are paired with the source data.

Non-generative models: A deep feature extractor learns a discriminative representation using the labels in the source and maps the target data to the same space through a domain-confusion loss. An initial work, with focus on semantic segmentation, based on this concept is proposed by Hoffman *et al.* [Ho16]. They applied category updates on the target images, using a constrained pixel-wise multiple instance learning objective. Ganin *et al.* [GL15] introduced the Domain-Adversarial Neural Network (DANN), which consists of shared feature extraction layers and two classifiers, which integrate a gradient reversal layer (GRL) into the standard architecture to ensure that the feature distributions over the two domains are made similar. In the same context, Tsai *et al.* [Ts18] proposed a Non-generative Adversarial Learning Model (NALM) for semantic segmentation. Their model consists of two modules: A segmentation network G and a discriminator D. The source image I_s is forwarded (with labels) to the segmentation network for optimizing G. Then, the segmentation soft-max output P_t for the target image I_t (without label) is predicted. These two predictions are forwarded to the discriminator D to distinguish whether the input is from the source or the target domain. With an adversarial loss on the target prediction, the network propagates gradients from D to G, which would encourage G to generate segmentation distributions in the target domain similar to the source prediction. The adaptation is done using two loss functions as follows:

$$L_{seg}(I_s) = -\sum_{h,w}\sum_{c \in C} {Y_s}^{(h,w,c)} \log({P_s}^{(h,w,c)}), \tag{3}$$

$$L_{adv}(I_t) = -\sum_{h,w} \log(D(P_t)^{(h,w,1)}), \tag{4}$$

$$L(I_s, I_t) = \sum_i {\lambda^i}_{seg}\, {L^i}_{seg}(I_s) + \sum_i {\lambda^i}_{adv}\, {L^i}_{adv}(I_t), \tag{5}$$

where Y_s is the label for the source images, $P_s = G(I_s)$ is the segmentation output, C is the number of categories, and λ is a weighting factor.

2.3 Homogeneous adversarial-reconstruction approaches

Inspired by dual learning [He16], adversarial-reconstruction is proposed in deep DA with the help of dual GAN models. Zhu *et al.* [Zh17] proposed a Cycle Generative Adversarial Network (CycleGAN) that can translate the distinctives of one domain into the other (without requiring paired images), applying inverse mapping and using a cycle consistency loss. They used a class-balanced self-training framework to avoid the gradual dominance of large classes in pseudo-label generation, and utilized spatial priors to refine the generated pseudo-labels [Zo18]. The model has two generators, which learn a mapping $G : X \to Y$ and an inverse mapping $F : Y \to X$. Two discriminators, D_X and D_Y measure how realistic the generated images are $G(X) \approx Y$ or $G(Y) \approx X$ by an adversarial loss, and how well the input is reconstructed after a sequence of two generations $F(G(X)) \approx X$ or $G(F(Y)) \approx Y$ by a cycle consistency loss (reconstruction loss). Thus, the distribution of images from $G(X)$ or $F(Y)$ is indistinguishable from the distribution Y or X:

$$L_{gan}(G, D_Y, X, Y) = \mathbb{E}_y[log D_Y(y)] + \mathbb{E}_x[log(1 - D_Y(G(x)))], \tag{6}$$

$$L_{cyc}(G, F) = \mathbb{E}_x[||F(G(x)) - x||_1] + \mathbb{E}_y[||G(F(y)) - y||_1], \tag{7}$$

$$L(G, F, D_X, D_Y) = L_{gan}(G, D_Y, X, Y) + L_{gan}(F, D_X, Y, X) + \lambda L_{cyc}(G, F), \tag{8}$$

where L_{gan} is the adversarial loss produced by discriminator D_Y with mapping function $G: X \rightarrow Y$, L_{cyc} is the reconstruction loss, and λ is a weighting factor. Similarly, CyCADA [Ho18] uses the CycleGAN [Zh17] to generate extra training data through an adversarial learning framework. A current variant of this model [Le18] proposes a Diverse Image-to-image Translation via Disentangled Representations (DITDR). The model disentangles the latent spaces of source and target into a shared content space and an attribute space. Adaptation then is done using cross-cycle consistency loss.

2.4 Heterogeneous DDA

Unlike the homogeneous DA, in heterogeneous DA the dimensions of the feature spaces in the source domain may differ from those in the target. Thus, discrepancy-based methods fail to work without extra processes. Shu *et al.* [Sh15] proposed weakly shared networks to transfer labeled information across heterogeneous domains, in particular, from the text domain to the image domain. Chen *et al.* [Ch16] proposed Transfer Neural Trees (TNTs), which consist of two stream networks to learn a domain-invariant feature representation for each modality. When images in two different domains can be directly resized into an identical dimension, Class criterion and Statistic criterion methods are still effective. In their work, Gatys *et al.* [ASB15] suggested that content and style are separable in CNNs. Accordingly, they proposed a Neural Style Transfer (NST) model. They showed that the higher layers of the networks can capture the content representations, and the style (texture) features can be generated by including the filter responses over the spatial extent of the feature maps within the networks. In this way, responses in a layer l can be stored in a matrix F_l, where F^l_{ij} is the activation of the i^{th} filter at position j in the layer l. The feature correlations are given by the Gram matrix G_l, where G^l_{ij} is the inner product between the vectorized feature map i and j in the layer l as: $G^l_{ij} = \sum_k F^l_{ik} F^l_{jk}$. To generate a texture that matches the style of a given image, they used gradient descent from a white noise image to find an image that matches the style representation of the original image. This is done by minimizing the mean-squared distance between the entries of the Gram matrixes. The limited works which are proposed based on adversarial and reconstruction based approaches for heterogeneous domain adaptation, are mainly focused on utilizing the homogeneous DDA models to transfer between the heterogeneous data domains.

3 Experiments

As the main objective of this work, we picked some DDA methods which possess certain criteria such as: Using a fully unsupervised scheme, providing unpaired image-to-image adaptation, delivering pixel level semantic affinity between the adapted domains, to be evaluated for domain adaptation in CNN based iris segmentation. Delivering promising results already in the original works, we considered: NALM [Ts18], CycleGAN [Zh17], DITDR [Le18], and NST [ASB15]. The technical details and the actual DDA approach used in each method are already discussed in Section 2. In the following we present the corresponding experiments we curried out, and analyze and discuss the results in each case.

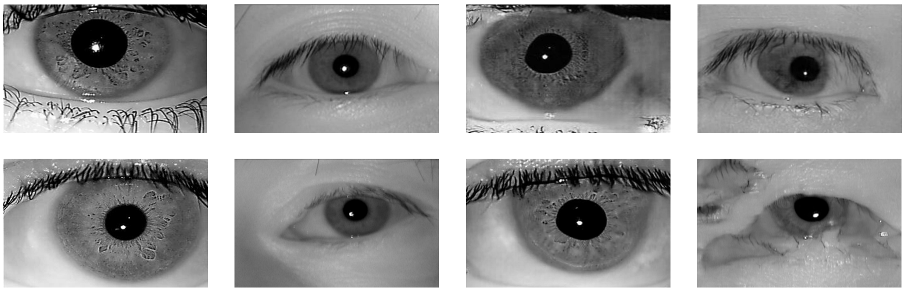


Fig. 1: Sample images from IITD and Casia5a databases (first and second columns), and their corresponding adaptations using CycleGAN and DITDR models (third and fourth columns) respectively.

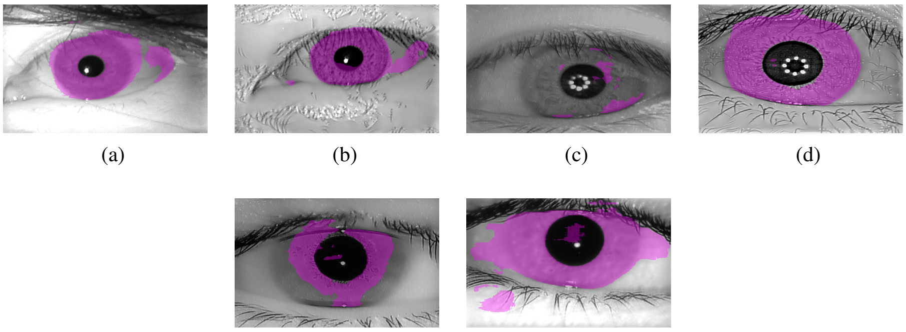
3.1 Experimental framework

For our experiments we used three publicly available iris databases. The Casia4i[3] database (containing 2640 images belonging to 249 subjects), the IITD[4] database (containing 2240 images belonging to 224 subjects), and the Casia5a[5] database (containing 1880 images belonging to 47 subjects). The details of these databases can be found in the provided links. The segmentation ground-truth masks for these databases were provided by the University of Salzburg[6]. For the experiments, we developed six sets of unique database pairs, using the three available databases, terming them as "TargetToSource". So, in each experiment we adapted from the "Target" database (for which the labels are not available) to the "Source" database (for which the labels are available). We performed the adaptations assigning each sample in the source database to a sample in the target database (randomly) for the image-to-image translation schemes. To evaluate the performance of DDA algorithms, which do not generate the segmentation masks of the target data, we considered to apply a Fully Convolutional Neural Network (FCN), which has been already used for iris segmentation successfully [JU17], to the adapted outputs. Iris segmentation accuracies were evaluated using $nice1$ and $nice2$ segmentation scores based on the NICE-I protocol[7]. The segmentation error score $nice1$ calculates the proportion of corresponding disagreeing pixels (by the logical exclusive-or operator) over all the image as follows:

$$nice1 = \frac{1}{c \times r} \sum_{c'} \sum_{r'} O(c', r') \otimes C(c', r'), \tag{9}$$

where c and r are the columns and rows of the segmentation masks, and $O(c', r')$ and $C(c', r')$ are, respectively, pixels of the output and the ground-truth mask. The second seg-

[3] http://biometrics.idealtest.org
[4] http://www4.comp.polyu.edu.hk/ csajaykr/database.php
[5] http://www.biometrics.idealtest.org
[6] http://www.wavelab.at/sources/Hofbauer14b
[7] http://nice1.di.ubi.pt/evaluation.htm



(a) (b) (c) (d) (e) (f)

Fig. 2: Sample adapted images for: Casia5aToCasia4i (2a), Casia5aToIITD (2b), Casia4iToCasia5a (2c), Casia4iToIITD (2d), IITDToCasia5a (2e), IITDToCasia4i (2f) using NST.

mentation error score (*nice*2) is the average between the false-positive (FPP) and false-negative (FNP) segmented iris pixels:

$$nice2 = \frac{1}{2}\left(FPP + FNP\right) \tag{10}$$

The values of *nice*1 and *nice*2 are bounded in the [0, 1] interval, and in this context, ”1” and ”0” are respectively the worst and the optimal values.

3.2 Evaluations and analysis

Fig.1 (first row) demonstrates examplary results we obtained after adaptation between the databases using CycleGAN. As it can be seen in the figure, the model is not able to preserve the geometric properties of the image contents (*i.e.* iris circle shape) in the reconstructed images. This is true also for the iris texture, which holds the unique information utilized for recognition. While the texture information could be retrieved (*e.g.* by superposition of the segmentation mask on the original input), yet the accurate iris pixel localization (as the key objective of the iris segmentation) is not addressed. The second row in Fig.1 shows examplary results for applying the DITDR model to our experimental databases. As it can be seen, this model also suffers from the same drawbacks as the CycleGAN model. To this extent, the GAN based models seem not be a good choice for our segmentation purpose.

Fig.2 demonstrates example results we obtained by applying the NST model to our experimental data. As it can be seen, while there exist some artifacts (as propagated target image contents) in an adapted output (Casia5aToIITD), yet the model is able to preserve the key source eye structure contents in the adapted images to a great extent, affirming the model’s capability to split and propagate the content and style information successfully. In order to examine the actual expediency of this model on our experimental data, we applied our

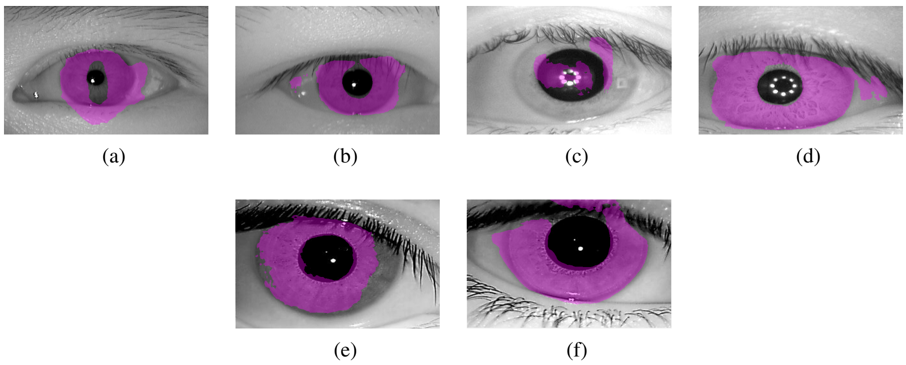


Fig. 3: Sample adapted images for: Casia5aToCasia4i (3a), Casia5aToIITD (3b), Casia4iToCasia5a (3c), Casia4iToIITD (3d), IITDToCasia5a (3e), IITDToCasia4i (3f) using NALM.

FCN model to the adapted outputs and evaluated the segmentation performance in each case. Tab.1 demonstrates the results for these experiments. As it can be seen in the table, adoptions seem to deliver promising results, compared to the baseline (results of applying the network trained with the source data, directly to the target data), in some certain cases (*i.e*. Casia5aToCasia4i, Casia4iToIITD, and IITDToCasia4i), but not all. Comparing the results to those of the shallow DA algorithm [JUK17] (the non-linear method is considered, as it delivered better results in the majority of cases), the NST model mainly shows better performance adapting between Casia4i and IITD databases.

Likewise, we applied the NALM algorithm to our databases. As the corresponding results in Tab.1 demonstrate, the algorithm is able to adapt the domains successfully in the majority of cases. The model obtains an acceptable segmentation score (slighter lower than the

Method	NST		NALM		[JUK17]		Baseline	
Scores	nice1	nice2	nice1	nice2	nice1	nice2	nice1	nice2
Casia5aToCasia4i	0.14	0.30	0.21	0.36	0.02	0.07	0.27	0.40
Casia5aToIITD	0.05	0.16	0.07	0.22	0.03	0.08	0.04	0.11
Casia4iToCasia5a	0.30	0.62	0.29	0.61	0.27	0.35	0.29	0.64
Casia4iToIITD	0.10	0.09	0.17	0.19	0.20	0.17	0.31	0.58
IITDToCasia5a	0.24	0.22	0.15	0.21	0.26	0.30	0.22	0.22
IITDToCasia4i	0.08	0.10	0.07	0.10	0.10	0.09	0.21	0.21

Tab. 1: Segmentation scores for NST, NALM, and [JUK17] (Nonlinear) methods against the baseline.

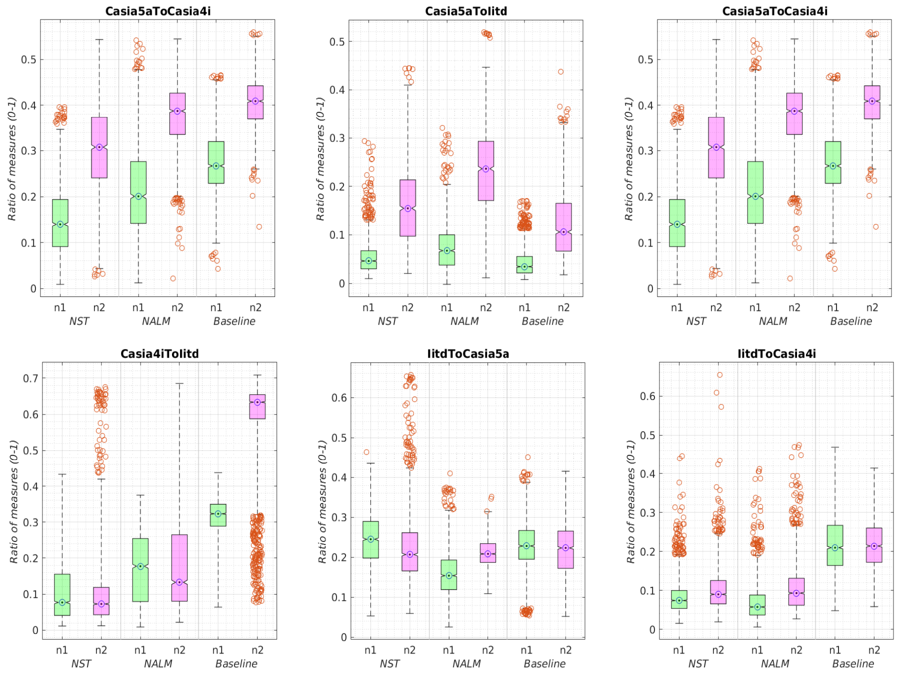


Fig. 4: Experimental results of NST and NALM methods against the Baseline results.

baseline) also on Casia5a when trained on the IITD labeled data (check Fig.3 for corresponding examplary segmentation outputs). Comparing the results to those of the shallow algorithm ([JUK17]), the model delivers a comparable adaptation (to the NST model) profile also, as it delivers better performance in 3 (out of 6) adaptation experiments. Fig. 4 provides further details on each experiment in the form of boxplots.

To further assess the actual performance of the proposed adaptation methods within an iris segmentation framework, we considered to compare the obtained segmentation results to the results obtained by applying: Some traditional iris segmentation algorithms (namely: Osiris (Viterbi algorithm on the gradient map of anisotropic smoothed iris) [ODGS16], Caht (contrast-adjusted hough transform) [RUW13], and Wahet (weighted adaptive Hough and ellipsopolar transform) [UW12]), as well as our FCN network (when trained and tested on an identical database, assuming that the training labels are available), to the experimental databases. TABLE 2 demonstrates the results for these experiments. Expectedly, FCN network shows superior performance over all other algorithms (including the traditional algorithms, and the corresponding deep methods). Comparing the results obtained by the traditional algorithms against those obtained using DDA methods, we can observe better performance by NST method on the Casia4i database (in particular when adapting it into the IITD database domain), compared to Wahet algorithm, and also on the IITD database (when adapting it into Casia4i database domain), compared to both Wahet and Caht al-

Method	Osiris		Caht		Wahet		FCN	
Scores	nice1	nice2	nice1	nice2	nice1	nice2	nice1	nice2
Casia5a	0.018	0.033	0.036	0.151	0.024	0.083	0.008	0.002
Casia4i	0.056	0.067	0116	0.147	0.060	0.084	0.044	0.043
IITD	0.055	0.075	0.113	0.156	0.137	0.176	0.053	0.059

Tab. 2: Segmentation scores obtained by applying Osiris, Wahet, Cahet, and FCN network on the experimental databases.

gorithms. Likewise, the NALM algorithm shows promising performance on this database compared to both Wahet and Caht algorithms.

4 Discussion and conclusion

Analysis of the results obtained shows that the models which are able to split and treat the content and the texture information (*i.e.* NST), perform comparably better on iris domains possessing diverged (heterogeneous) feature spaces. The better results obtained by the NST model, adapting the Casia5a domain to other two databases' domains (*i.e.* Casi5aToCasia4i or Casi5aToIITD) support this concept, as the feature (content) space of this database diverges significantly from the other two databases (check the examplary images in Fig.1). On the other hand, NALM model delivers promising results mostly on databases that possess higher content affinities (*e.g.* IITDToCasia4i). Nonetheless, both approaches obtained promising results adapting between Casia4i and IITD databases, performing superior to the shallow method [JUK17], as well as the baseline in this case (see TABLE 1). It should be noted that (as a key strength) in these approaches no target label data is used in the adaptation process. The worst results for both approaches (expectedly) are obtained on Casia4iToCasia5a adaptation. This seems to be due to the high divergence of the feature spaces between these two databases, and the subsequent difficulties networks have to learn the mapping from Casia4i to Casia5a (than the inverse case). Overall, evaluation of the results obtained against the baseline leads us to the conclusion that: Regardless of the approach used, generally domain adaptation between databases which enjoy higher feature (content) affinities delivers better results and vice versa. Furthermore, while experimental results proved expediency of existing (evaluated) unsupervised DDA models, yet in most cases, the adaptations and their subsequent segmentation outputs were far from the optimal (to be used for recognition). This clearly shows that many issues still remain to be addressed in this field when it comes to CNN based iris segmentation, when no training labels are available. Analyzing the performance, we can also predict that unsupervised-heterogeneous deep DA methods would attract more attention for CNN based iris segmentation applications in future.

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