Domain Adaptation for CNN Based Iris Segmentation

Ehsaneddin Jalilian¹, Andreas Uhl¹ and Roland Kwitt¹

¹Department of Computer Sciences
University of Salzburg
Salzburg, Austria

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4. Non-linear Domain Adaptation

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Introduction

Convolutional neural networks (CNNs) and iris segmentation

- CNNs demonstrated considerable success in solving key artificial vision challenges such as object detection, recognition, and segmentation.
- Segmentation of iris texture in eye images is a key problem in iris recognition, which plays vital role in accuracy of the system.
- In recent years, application of CNNs for iris segmentation has received some research attention[1] [2]

Problem statement

- Training CNNs requires adequate amount of labeled data.
- Data labeling is extremely expensive and time-consuming process.
- To confront this issue, we considered to adapt the domains of available labeled data to those of the targets, and train CNNs with the adapted data, and segment the target data, eliminating the need for the target data labels.
Domain adaptation

- Given a source database \((X_s, Y_s, P(X_s))\) and a target database \((X_t, Y_t, P(X_t))\)
- Under the domain difference scenario, we assume the conditional distributions of \(Y_s\) and \(Y_t\) are the same, but the marginal distributions of \(X_s\) and \(X_t\) differ in the two domains
- The distinction between two distributions is referred to as sample bias \(\phi\) so as:

\[
P_t = P_s(\phi(X_s), Y_s).
\] (1)

CNN based domain adaptation

- Using empirical risk minimization framework for supervised learning, we want to select an optimal parameter \(\psi'\), to minimize the following objective function

\[
\psi'_t = \arg \min_{\psi \in \Psi} \sum_{(x, y) \in X \times Y} \tilde{P}_s(\phi(X_s), Y_s) g(x, y, \psi) = \arg \min_{\psi \in \Psi} \sum_{i=1}^{N} g(\phi(x_s), y_s, \psi).
\] (2)

- Weighting the images’ intensities of source data by \(\phi\) provides the solution to the minimization function
Linear intensity transfer

- Straight forward solution to weight the intensities of source data is using a linear normalization model:

\[ b = (\max(B) - \min(B)) \frac{a - \min(A)}{\max(A) - \min(A)} + \min(B). \]  

- Extract the intensity ranges of iris, non-iris, pupil regions in the target database.
- Using this model, adapt the intensities in source data to those of the target.
- Train the network with the adapted data and test it on the targets.
Linear Domain Adaptation

Experimental framework

- Databases: Casia4i database\(^1\), ltitd database\(^2\), Casia5a database\(^3\)
- Metrics: Segmentation error scores: nice1, nice2\(^4\), and F1 score
- Network: Fully Convolutional Encoder-Decoder Network (FCN) [3]

<table>
<thead>
<tr>
<th>Method</th>
<th>Adapted-target</th>
<th>Baseline(Source-target)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>nice1</td>
<td>nice2</td>
</tr>
<tr>
<td>Casia5a-casia4i</td>
<td>0.186</td>
<td>0.220</td>
</tr>
<tr>
<td>Casia5a-ltitd</td>
<td>0.148</td>
<td>0.172</td>
</tr>
<tr>
<td>Casia4i-casia5a</td>
<td>0.066</td>
<td>0.194</td>
</tr>
<tr>
<td>Casia4i-ltitd</td>
<td>0.121</td>
<td>0.141</td>
</tr>
<tr>
<td>ltitd-casia5a</td>
<td>0.062</td>
<td>0.185</td>
</tr>
<tr>
<td>ltitd-casia4i</td>
<td>0.299</td>
<td>0.319</td>
</tr>
</tbody>
</table>

**Table:** Segmentation scores for the linear-based domain adaptation method against the baseline (source-target) results

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\(^1\) [http://biometrics.idealtest.org](http://biometrics.idealtest.org)


\(^3\) [http://www.biometrics.idealtest.org](http://www.biometrics.idealtest.org)

\(^4\) [http://nice1.di.ubi.pt/dates.htm](http://nice1.di.ubi.pt/dates.htm)
Linear Adaptation Experiment

<table>
<thead>
<tr>
<th>Source images</th>
<th>Adapted images</th>
<th>Target images</th>
<th>Ground truths</th>
<th>Result masks</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="source_1.png" alt="Source Image" /></td>
<td><img src="adapted_1.png" alt="Adapted Image" /></td>
<td><img src="target_1.png" alt="Target Image" /></td>
<td><img src="ground_1.png" alt="Ground Truth" /></td>
<td><img src="result_1.png" alt="Result Mask" /></td>
</tr>
<tr>
<td><img src="source_2.png" alt="Source Image" /></td>
<td><img src="adapted_2.png" alt="Adapted Image" /></td>
<td><img src="target_2.png" alt="Target Image" /></td>
<td><img src="ground_2.png" alt="Ground Truth" /></td>
<td><img src="result_2.png" alt="Result Mask" /></td>
</tr>
<tr>
<td><img src="source_3.png" alt="Source Image" /></td>
<td><img src="adapted_3.png" alt="Adapted Image" /></td>
<td><img src="target_3.png" alt="Target Image" /></td>
<td><img src="ground_3.png" alt="Ground Truth" /></td>
<td><img src="result_3.png" alt="Result Mask" /></td>
</tr>
</tbody>
</table>

Figure: Sample adapted images and their corresponding segmentation results for Casia4i-Iitd (first row), Iitd-Casia5a (second row), and Casia5a-Casia4i (third row) database pairs (source-target) using the linear domain adaptation method.
Non-linear intensity transfer

- In the linear adaptation, all the source intensity ranges get normalized to "a single average intensity range of that region in the target database"
- The target intensity ranges follow a non-linear distribution
- To address this, calculate the mean of corresponding minimum values and apply kernel smoothing regression on the data to get a polynomial function $f(x)$:
  \[
  f(x) = p_1 x^n + p_2 x^{n-1} + \ldots + p_n x + p_{n+1}.
  \] (4)
- Select a min for each sample, and estimated the max using the polynomial

**Figure**: Sample non-linear data adaptation steps
Non-linear Damion Adaptation

<table>
<thead>
<tr>
<th>Method</th>
<th>Adapted-target (NB)</th>
<th>Baseline(Source-target)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>nice1</td>
<td>nice2</td>
</tr>
<tr>
<td>Casia5a-casia4i</td>
<td>0.274</td>
<td>0.353</td>
</tr>
<tr>
<td>Casia5a-iitd</td>
<td>0.266</td>
<td>0.305</td>
</tr>
<tr>
<td>Casia4i-casia5a</td>
<td>0.027</td>
<td>0.074</td>
</tr>
<tr>
<td>Casia4i-iitd</td>
<td>0.102</td>
<td>0.095</td>
</tr>
<tr>
<td>litd-casia5a</td>
<td>0.034</td>
<td>0.088</td>
</tr>
<tr>
<td>litd-casia4i</td>
<td>0.208</td>
<td>0.174</td>
</tr>
</tbody>
</table>

Table: Segmentation scores for the non-linear-based domain adaptation method against the baseline (source-target) results.
Figure: Sample adapted images and their corresponding segmentation results for Casia4i-Iitd (first row), Iitd-Casia5a (second row), and Casia5a-Casia4i (third row) database pairs (source-target) using the non-linear domain adaptation method.
Training with minimum labeled data

- With the aim of minimizing the number of labeled data required to train the FCN, and maintaining optimal segmentation scores
- Decreased the number of labeled samples required to train the FCN stepwise
- Tested the FCN on the corresponding databases

<table>
<thead>
<tr>
<th>Database</th>
<th>Casia5a</th>
<th>Casia4i</th>
<th>Iiitd</th>
</tr>
</thead>
<tbody>
<tr>
<td>Score</td>
<td>nice1</td>
<td>nice2</td>
<td>f1</td>
</tr>
<tr>
<td>15 pcs</td>
<td>0.075</td>
<td>0.082</td>
<td>0.875</td>
</tr>
<tr>
<td>25 pcs</td>
<td>0.064</td>
<td>0.077</td>
<td>0.896</td>
</tr>
<tr>
<td>50 pcs</td>
<td>0.050</td>
<td>0.070</td>
<td>0.909</td>
</tr>
<tr>
<td>100 pcs</td>
<td>0.021</td>
<td>0.040</td>
<td>0.921</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Method</th>
<th>target -target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scores</td>
<td>nice1</td>
</tr>
<tr>
<td>Casia5a-casia5a</td>
<td>0.019</td>
</tr>
<tr>
<td>Casia4i-casia4i</td>
<td>0.033</td>
</tr>
<tr>
<td>Iiitd-iitd</td>
<td>0.027</td>
</tr>
</tbody>
</table>

- Optimal segmentation scores can be achieved using (ap) 100 training samples
- Slightly lower, but very close scores can be achieved with 50 to 25 samples
Conclusion and Future Work

Conclusion

- We proposed two domain adaptation methods for CNN based iris segmentation.
- Feature representations affecting the weights during training process are not limited to tonal distributions, and further features such as geometric properties of iris, non-iris, and pupil are definitely affecting this process.
- Tonal distribution (intensity ranges of iris, non-iris, and pupil) plays a key role in generalization of FCNs on new iris data that differs from the training data.

Future work

- We will investigate the relations between the two proposed methods and the reasons for the different results.
- We also explore more feature representations which encourage further distinctions between two domains, hoping to be able to develop a more comprehensive domain adaptation method.
Thank you, Remarks?
Ehsaneddin Jalilian and Andreas Uhl.
Iris segmentation using fully convolutional encoder–decoder networks.

Nianfeng Liu, Haiqing Li, Man Zhang, Jing Liu, Zhenan Sun, and Tieniu Tan.
Accurate iris segmentation in non-cooperative environments using fully convolutional networks.

Vijay Badrinarayanan, Alex Kendall, and Roberto Cipolla.
Segnet: A deep convolutional encoder-decoder architecture for image segmentation.