Automatic Infant Face Verification via Convolutional Neural Networks

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Abstract

In this paper, we investigate how convolutional neural networks (CNN) can learn to solve the verification task for faces of young children. One of the main issues of automatic face verification approaches is how to deal with facial changes resulting from aging. Since the facial shape and features change drastically during early childhood, the recognition of children can be challenging even for human observers. Therefore, we design CNNs that take two infant photographs as input and verify whether they belong to the same child. To specifically train our CNNs to recognize young children, we collect a new infant face dataset including 4,528 face images of 42 subjects in the age range of 0 to 6 years. Our results show an accuracy of up to 85 percent for face verification using our dataset with no overlapping subjects between the training and test data, and 72 percent in the FG-NET dataset for the age range from 0 to 4 years.

Categories and Subject Descriptors (according to ACM CCS): I.5.4 [Pattern Recognition]: Application—Computer Vision

1. Introduction

From automatic tagging of friends on pictures for social networks or the recognition of wanted criminals on surveillance cameras to automated searching for missing children and their identification - in many situations it is necessary to verify whether two images show the same person or not. Due to this strong demand for face recognition and verification applications, many different solutions have been proposed during the last years. Especially the development of new deep learning tools and algorithms has brought the accuracy of automatic face recognition systems to a new level [SCWT14], displaying nearly human-like performance on face recognition benchmarks like LFW [HRBL15], MegaFace [KSMB15], FGNET [fgr] and AgeDB [MPS17].

However, if it is necessary to verify a person after time has passed and the person has aged, robust age-invariant face recognition and verification is still unreached. Major facial changes include growing of the face, and changes to the shape and appearance which need to be counterbalanced prior or during the recognition process. While aging might already pose problems when recognizing adult subjects, this task can be even more difficult for children and infants. For very young children, facial aging is a complex process that involves substantive facial growing and shape changes. This makes the verification of children which have aged only a few years challenging even for human subjects. Fig. 1 shows an example of major facial changes during early childhood by using a child from the FGNET dataset at the age of 1, 3, and 5, respectively.

Moreover, there is relative few data available to build reasonable models considering children in early childhood. Most publicly available aging datasets are limited in age range and focus on adults or have only a few samples per age, reducing their applicability for deep learning approaches. To the best of our knowledge, the only public domain aging dataset which includes images of children at different ages is the FGNET dataset containing a small number of images from subjects with 12 age-separated images per subject, including 269 images of 75 subjects in the age span of 0 to 6 years. Even considering data augmentation techniques, this amount of data is not sufficient to train a deep neural network.

In this paper we specifically focus on this challenging case and investigate whether verification network can be used for age-invariant infant facial verification, using facial features learned from a dataset with face images of young children. The problem of age-invariant face recognition was described in previous work using either vision approaches [PTT16] or deep learning [WQL16]. As no sufficient dataset for training a deep neural network on infant images was available, previous work mainly focused on developing age-invariant features. For our CNN, we adopt the DeepID2 [SCWT14] network to extract facial features which are directly fed into a classification network to decide whether two presented images show the same child or not. For training, we create a novel dataset which contains 4528 face images of 42 children in the age range of 0 to 6 years and for each child include images at different ages. We split the dataset into a non-overlapping...
2. Related Work

Many approaches related to face aging have been proposed in the past, including age synthesis [RC06, GMP∗’06, FGH10, SMZ∗’07], prediction [SSSB07], as well as age-invariant [LXZ∗’16, WLQ16] or age-restricted [TSS12, BBVS16] classification. In this section we focus on approaches using convolutional neural networks that are more closely related to our paper. We begin with a short overview on traditional face classification and the approaches we used in our architecture and continue with neural network methods that focus on age invariant classification.

In recent years deep learning and especially convolutional neural networks have significantly improved the quality of face verification applications and systems. Initially, most methods focused on recognition tasks without considering cross-age applications. Among these deep learning works, a discriminative deep metric learning method [HLT14] was presented for face verification that aimed to find a Mahalanobis distance metric to maximize the inter-class variations and minimize the intra-class variations. Taigman et al. [TYRW14] introduced a multi-stage method also called DeepFace that aligns faces to a general 3D shape model and trains a multi-class Siamese Network [CCHL05] to optimizes the Euclidean distance between two facial features. FaceNet [SKP15] minimizes the deep triple facial metrics by learning the distance between the positive pairs and negative pairs. In addition, using 128 bytes per face the performance of the method is cost efficient. An innovative loss function called center-loss was proposed in [WZL16], that efficiently increases inter-class dispersion and intra-class compactness. In [SWT14, SCWT14] facial feature extractors based on CNNs, named DeepID and DeepID2 respectively, were introduced. Especially DeepID2 aimed to enlarge the inter-personal variances extracted from different identities and reduced the intra-personal variances extracted from the same identity. While all of these approaches greatly contributed to face recognition, we additionally focus on age-invariant recognition for children.

Recently, deep learning models were also used for age-invariant recognition tasks. Usually, approaches for this task either extract information from face images to build age-invariant face features or build age-invariant face models for the matching decision. Focusing on age-invariant features, Wen et al. [WLQ16] proposed a latent factor guided CNN framework to directly learn age-invariant deep face features. The authors analyzed the results for different age groups. While they achieved good performance, the results reported for young children from 0 to 4 years were worse than for older age groups. Other work focused on deep learning age-invariant features by using an age-estimation step to remove aging factors from the extracted facial features [ZDH17] or utilized multi-task learning to improve extracted features [WZK∗’17]. In contrast to the development of age-invariant features, we focus on investigating whether a previously established face feature extractor based on DeepID2 can also be used for age-invariant recognition of infants. Specifically, we combine DeepID2 features with a classification network and train end-to-end on a dataset containing facial images of young children.

Other age-invariant face recognition frameworks focused on face modeling or synthesis for target ages. In [ABD17] the generation of faces at different ages was done via a generative adversarial network. While the quality of the generated faces is overall convincing, the faces cannot easily be used for feature extraction as they still differ from real faces. As a different modeling approach, Temporal Non-Volume Preserving transformations were introduced [DQL∗’17], which performed well on cross-age verification tasks. Liu et al. [LXZ∗’16] proposed to combine age-invariant face modeling and feature matching to solve face verification for large age gaps. Face images for 4 different age groups are modeled for each input image resulting in 4 synthesized image pairs and one original pair that are fed into parallel feature extraction CNNs. In contrast to this work, we only focus on the age category of children and aim to robustly identify children for small and large age gaps. Therefore, our input images would already lie in the same age category and would not benefit from the proposed face synthesis. Our proposed feature extraction part is similar to the parallel networks including the idea to subtract the obtained features from each other. However, instead of only using a Softmax to decide whether the images match or not, we apply a classification network after feature extraction in order to achieve robust results within the same age category.

Overall, our paper focuses on the challenging infant face verification through a deep learning method. We directly use the im-
ages as input for our feature extraction CNN and therefore prevent the need of face synthesis or a hand-crafted feature descriptor. Instead we investigate whether CNN features can be directly combined with CNN classification networks to solve the age-invariant face verification task for young children.

3. Infant Face Dataset

In order to investigate whether a CNN can be trained to identify young children at different ages we create a new dataset. As face features vary, especially during early childhood, we only include infants of the age 0 to 6 in our dataset. Overall our infant dataset consists of 4528 face images with a size of 128 × 128 pixels featuring 42 children, including 24 (57%) girls and 18 (43%) boys as well as 2 pairs of sisters and a pair of brother and sister. For all children, images at different ages are included in the dataset.

We first select YouTube videos that show infants at different stages of their development. Our face preprocessing pipeline is inspired by DeepFace [TYRW14], however we use different techniques for each preprocessing step. To collect face information from the chosen videos we use the Histogram of Oriented Gradients algorithm [JDT05] and employ its to detect face contours in every frame. While this already provides facial regions which could be cropped from the image and used to train CNNs, further data normalization can improve the training process. Therefore, we align the face images to increase the training performance as proposed by Sun et al. [TYRW14]. Since both eyes of the face should be on the same horizontal line it is necessary to extract facial landmarks within the previously detected facial region. This is done using the Ensemble of Regression Trees [KS14] algorithm, which detects 68 facial feature points. Afterwards the image is aligned using similarity transformations and cropped based on the area which contains the facial landmarks. Images that cannot be aligned are removed from the dataset. An overview of the preprocessing steps is presented in Fig. 2. For both the HOG and Ensemble of Regression Trees algorithm we use the implementation of the Dlib library [Kin09].

Once the cropped face images are computed, we manually clean the data to remove duplicates and images with insufficient resolution. Finally, each image in the database is labeled with an ID for the represented child and an index. However, the data in our new infant face database is still unbalanced. To balance the data, we perform upsampling to augment the number of face images for children with less than 100 face images to reach 100 face images.

We split our dataset into a training set containing around 3500 images and a test set containing around 1200 images. The training and test split is non-overlapping, therefore each child is exclusively either in the training or test set. We randomly chose 31 children for the training set and use the images of the other 11 children in the test set. For both sets, we randomly generate positive and negative face pairs. The number of positive and negative face pairs is the same in order to avoid training problems due to imbalanced data. Overall, the training set contains 128,000 pairs, while test set contains 32,000 pairs.

4. Network Architecture

We use CNNs for the infant face verification task by presenting two face images to the network and deciding whether these belong to the same child. Our CNN architecture consists of two parts as shown in Fig. 3: In the first part we perform feature extraction by applying DeepID2 [SCWT14] in a Siamese network style [CHL05], in the second part we perform similarity learning on the features as shown in Fig. 5. The input to the network is a pair of RGB images of size 128 × 128 pixels and the output is a probability score indicating whether the same child is presented on the images. Overall, the feature extraction network learns high-level discriminative infant face features, which are afterwards fed to a classification network that predicts the similarity of both learned features respectively.

4.1. Facial Features Extraction

Our network structure for infant facial feature learning is adapted from DeepID2 [SCWT14], which performs deep face features extraction and has shown outstanding performance for the face verification task. Instead of treating the output as a one dimensional vector of facial features which would be obtained by applying a fully-connected layer, we compute a three dimensional feature matrix by summing up the last convolutional layer and max pooling layer. We chose this option, since we want to keep the features' local information when we input them into the following classification part. An overview of the feature extraction network's architecture is given in Figure 4. As we want to use two images, we use two branches each containing the feature extraction network and apply weight sharing similar to the Siamese network [CHL05]. In the end the obtained features are subtracted from each other before passing them to the classification part. An additional experiment has shown that using the difference instead of a concatenation delivers slightly better results for our architecture. Subtracting the feature vectors instead of concatenating them may avoid a possible local minimum during training.

4.2. Similarity Learning

After we obtain infant face features from the feature extraction network, we need to perform similarity learning to decide whether or
Figure 3: Overview of the architecture for the whole network which receives two RGB images as input and predicts the probability that the same child is depicted in both images. The first part of the CNN is used to extract facial features from an input image by adapting DeepID2 and using it in two branches of the network. Afterwards, the obtained features from each branch are subtracted from each other before passing them to the classification part of the network. The final output of the network are two probability scores for match and non-match.

Figure 4: The architecture for the first part of our network. This part of the CNN is used to extract facial features from an input image. We adapt DeepID2 [SCWT14] to output 3-dimensional features instead of 1-dimensional features. In the last layer, the outputs of Convolutional layer 4 (Conv4) and Max-pooling layer 3 (Pool3) are summed up to form a representative feature cuboid.

4.2.1. Network Architecture with Residual Units
We use Residual Units [HZRS16] which allows very deep network structures without performance degradation. The Residual Units enable the network to learn abstract and representative features and therefore produce a good classification performance. The proposed architecture of the residual classification network includes 18 convolutional layers and 7 Residual Units. We applied Parametric Rectified Linear Units (PReLU) [HZRS15] instead of Rectified Linear Units (ReLU) [NI06] as the activation functions. In contrast to ReLUs, PReLUs are able to retain negative values which might exist in the feature difference. The final classification is done using a Softmax layer. The full architecture details of the Residual Units network is described in Table 1.

4.2.2. Network Architecture with Inception Modules
In contrast to the idea of using several Residual Units to increase the depth of the network, Inception Modules [SLJ+15] enable larger receptive fields by using several multi-scale kernels in one module. This way information are based on a larger data region and more precise, however, the computation time and complexity is increased. Table 2 details the classification network architecture using Inception Modules. First, we want to feed the feature difference into an Inception Module with output sizes $14 \times 14 \times 512$. For a smoother transition of the initial feature size of $14 \times 14 \times 64$ to the target depth of 512, we employ two convolutional layers with a depth of 128 and 256 respectively, while keeping the height and width fixed. The convolutions in each Inception Module use filter sizes of $1 \times 1$, $3 \times 3$ and $5 \times 5$. Within the Inception Modules, convolutions with a kernel size of $1 \times 1$ extract information across all pixels and reduce the dimensionality of the output. Locating them
before the $3 \times 3$ and $5 \times 5$ convolutional layers significantly decreases computational cost. Afterwards, the convolutional layers with filter size of $3 \times 3$ and $5 \times 5$ cover larger pixel regions and extract their features. At the end of the classification architecture, we implement two fully-connected layers after the average pooling layer to get more abstract features. Finally, a Softmax is used to compute the probability of a match between the input images.

4.3. Training

We train our network consisting of feature extraction and classification end-to-end. For the loss calculation of the feature extraction network, we first convert the three dimensional feature representation into a one dimensional representation by concatenating the features into a column vector. This way, we are able to utilize the Contrastive Loss [HCL06]:

$$L_c = \frac{1}{2N} \sum_{n=1}^{N} (d - \beta \mathcal{Y})^2$$

(1)

where $N$ is the batch size which was set to 64 in our experiments, $d$ indicates the euclidean distance of two samples’ features and $\mathcal{Y} \in \{0, 1\}$ denotes whether the pair matches. The $\beta$ is a given threshold value, which is set to 1 in our experiments as proposed by Hadsell et al. [HCL06]. This loss efficiently reduces intra-personal variations while enlarging inter-personal variations. In combination with the larger feature vector this enables a more discriminative identity component.

Both variations of the classification network use the Softmax loss. The Softmax loss function is often used in CNNs for classification tasks to maximize the inter-class variations. For the Residual Units network the Softmax loss is computed at the end of the network and uses the same weight as the Contrastive Loss. The Inception Modules network uses an additional Softmax loss, since the Inception Modules network produces especially discriminate features in the middle layers. The additional Softmax loss is applied after the Inception (7d) layer for intermediate supervision. Overall the loss of our network can be denoted as

$$L = \alpha L_c + \beta L_1 + \gamma L_2$$

(2)

where $L_c$ is the Contrastive Loss from Eq. 1. Both $L_1$ and $L_2$ are Softmax losses, however, $L_2$ is used only in the Inception network after the Inception (7d) layer. For all our experiments we use $\alpha = 1$, $\beta = 1$ and $\gamma = 0.3$ as weights for the losses.

We use the Caffe [ISD+14] framework to implement our CNNs and use the same parameters for both versions. Before training, we perform data normalization by subtracting the mean color values as present in the training set. During training we create batches of images of size 64 and optimize using Stochastic Gradient Decent with an initial learning rate of 0.001, which was decreased using an inverse strategy. All network weights were initialized using the Xavier method [GB10]. To avoid the problem of vanishing gradients Batch Normalization [IS15] was applied. Furthermore, we prevent overfitting using Dropout [SHK+14]. Overall, the training process takes about 15 epochs for the Residual Units network and 10 epochs for the Inception Modules network. Training on a GeForce Titan X took about 15 minutes per epoch leading to a total training time of about 5 hours.

5. Experiments

In this section we present different experiments to investigate the effectiveness of our proposed network architectures on our infant face dataset and the infant subset of the FGNET dataset.

5.1. Experiments on our Infant Face Dataset

We first conduct experiments on the test set of our infant face dataset, to investigate the trainings result for both of the classification models. The achieved performance for both CNN models on our new infant face database is reported in Table 3. The proposed network combination of the adapted DeepID2 feature descriptor with Inception Modules achieves a verification accuracy of 85.3% and slightly outperforms the combination with Residual Units which achieves an accuracy of 84.01%. We additionally include experiments using the Siamese network of the Caffe framework with an Euclidean and Mahalanobis distance metric for feature matching, and a simplified architecture composed by the DeepID2-based feature extraction and a fully-connected layer with softmax, as baseline. The Mahalanobis metric achieves an accuracy of 77.9%, outperforming the Euclidean metric with an accuracy of 69.4%. The DeepID2-based architecture with a fully-connected layer achieves an accuracy of 78.8%. While the Siamese and fully-connected layer networks perform reasonable, our proposed networks outperforms them by a significant amount. Our results show that the classification of features which are not specifically designed to be age-invariant, can still offer promising results for age-invariant face verification of young children and infants.

5.2. Experiments on the Infant Subset of FGNET

We perform additional experiments on the FGNET [fgn] dataset to compare our method to a state-of-the-art CNN-based age-invariant face recognition proposed by Wen et al. [WLQ16]. They also present their results for very young children for the FGNET dataset, more specifically, for the age range from 0 to 4 years. As one of the public domain face aging datasets, the FGNET consists of 1002 face images from 82 different persons in age range of 0 to 69 years, but it only contains 193 face images for the age group of 0 to 4 years. Before we conduct the experiment, we perform the same preprocessing as for our own dataset as detailed in Section 3. Specifically, we use the HOG algorithm [DT05] to detect face regions and the algorithm Ensemble of Regression Trees [KSS14] to detect 68-points facial landmarks used to align the faces. We balance the data by upsampling face images to achieve the same of amount of images on each subject in order to randomly select face pairs with equal possibility.

Wen et al. [WLQ16] proposes a deep learning architecture to learn age-invariant features and achieves outstanding performance on the face recognition task. The authors trained their network (LF-CNN) on large scale web-collected face datasets. In contrast to our infant child dataset, these datasets do not focus on images of the same person at different and young ages. We present the results of the investigated network architectures as well as the Rank-1 identification accuracy as stated by LF-CNN in Table 4. Between our proposed architectures, the network architecture of our adapted DeepID2 features combined with an classification part containing
<table>
<thead>
<tr>
<th>Type</th>
<th>Output Size</th>
<th>Kernel Size</th>
<th>Stride</th>
<th>Padding</th>
</tr>
</thead>
<tbody>
<tr>
<td>Convolution (5)</td>
<td>14 x 14 x 128</td>
<td>3 x 3</td>
<td>1</td>
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<tr>
<td>Convolution (6)</td>
<td>12 x 12 x 256</td>
<td>3 x 3</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td><strong>3 Residual Units</strong></td>
<td>12 x 12 x 256</td>
<td>3 x 1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Convolution (7)</td>
<td>10 x 10 x 512</td>
<td>3 x 1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Max Pooling (7)</td>
<td>5 x 5 x 512</td>
<td>2 x 2</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td><strong>4 Residual Units</strong></td>
<td>5 x 5 x 512</td>
<td>3 x 1</td>
<td>1</td>
<td></td>
</tr>
<tr>
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<td>4 x 4 x 1024</td>
<td>2 x 1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Max Pooling (8)</td>
<td>2 x 2 x 1024</td>
<td>2 x 2</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Fully-Connected (9)</td>
<td>1 x 1 x 1024</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Fully-Connected (10)</td>
<td>1 x 1 x 4096</td>
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<tr>
<td>Fully-Connected (11)</td>
<td>1 x 1 x 2</td>
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Table 1: The architecture details of the classification network using Residual Units. Further parameters considering the detailed layout of the Residual Units are chosen as suggested by the ResNet [HZRS16] architecture.

<table>
<thead>
<tr>
<th>Type</th>
<th>Output Size</th>
<th>Kernel Size</th>
<th>Stride</th>
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<tr>
<td>Convolution (5)</td>
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<td>Convolution (6)</td>
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<tr>
<td>Inception (7a)</td>
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</tr>
<tr>
<td>Inception (7b)</td>
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<td>1</td>
</tr>
<tr>
<td>Inception (7c)</td>
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<td>Inception (7d)</td>
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<tr>
<td>Inception (7e)</td>
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<td>2</td>
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<tr>
<td>Max Pool</td>
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<td>3 x 3</td>
<td>2</td>
</tr>
<tr>
<td>Inception (8a)</td>
<td>7 x 7 x 832</td>
<td>3 x 3</td>
<td>2</td>
</tr>
<tr>
<td>Inception (8b)</td>
<td>7 x 7 x 1024</td>
<td>7 x 7</td>
<td>1</td>
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<td>Fully-Connected</td>
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<tr>
<td>Softmax</td>
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Table 2: The architecture details of the classification network using Inception Module. The number of kernels for each Inception Module are chosen as suggested by the GoogLeNet [SLJ15] architecture.

<table>
<thead>
<tr>
<th>Network Architecture</th>
<th>True-positive Rate</th>
<th>Acc.</th>
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<tr>
<td>Siamese+Euclidean metric</td>
<td>0.332</td>
<td>0.583</td>
</tr>
<tr>
<td>LF-CNNs [WLQ16] (Identification)</td>
<td>0.601</td>
<td>-</td>
</tr>
<tr>
<td>Ours (Residual Units)</td>
<td>0.665</td>
<td>0.694</td>
</tr>
<tr>
<td>Ours (Inception Modules)</td>
<td>0.709</td>
<td>0.726</td>
</tr>
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</table>

Table 4: The results of the infant face verification using our network architectures on the infant subset of the FGNET dataset. Here, we include the true-positive rate and compare it with the Rank-1 identification rate for LF-CNNs [WLQ16]. The accuracy values (Acc.) indicate the verification accuracy.

Inception Modules again achieves the best verification accuracy with 72.6% while the combination with Residual Units achieves 69.4% accuracy. In LF-CNN no accuracy was stated for the investigated age group. We used the true-positive rate to compare our networks with the Rank-1 identification result stated in LF-CNN. While the true-positive rate indicates the percentage of matches that were correctly identified as images of the same child, the Rank-1 identification rate denotes that the highest rated retrieved match is also the correct match. Using our networks, the best true-positive rate is also achieved by the Inception Modules network at 70.9% followed by the Residual Units network with 66.5%. Both networks outperform the Rank-1 identification rate of LF-CNN which is 60.1% on the infant age group of 0 to 4 years in the FGNET dataset, further supporting the idea of training standard facial feature extractors on infant child datasets. As the code of the LF-CNN network was not publicly available, we were not able to train their network on our infant child dataset and better distinguish the influence of using our dataset and our network architecture. Fig. 6 shows examples of image pairs that were not classified correctly by our network, illustrating false positives as well as false negatives. Most failure examples might be difficult to classify even for human observers due to the drastic changes of the infants facial shape.

We perform an additional Experiment on the FGNET dataset to further investigate the effects of our network using Inception Modules on age-invariant child verification. For this experiment we extract all images from our test set for a target age and compute the true-positive rates when testing with other age groups. For example, we chose each child at the age of 1 and pair it with all children at age 2 which yields a true-positive rate of 93%. In contrast, choosing a child at the age of 1 and forming pairs with all children at age 6 showed a true-positive rate of 84%. Table 5 shows the true-positive...
Figure 6: A demonstration for failure cases on the infant subset of the FGNET dataset. The subjects in this sub-dataset are in age range of 0 to 4 years and show drastic changes in their facial features.

Figure 7: An example for matched pairs that were correctly identified by our network. It is clearly visible how the facial features have changed and that verifying the child’s identity is more difficult for the larger age gap. Left: a child at 1 year and 6 years. Right: a child at 1 year and 2 years.

<table>
<thead>
<tr>
<th>Chosen Age</th>
<th>Tested Age</th>
<th>True-positive Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 year old</td>
<td>2 years old</td>
<td>0.93</td>
</tr>
<tr>
<td>1 year old</td>
<td>3 years old</td>
<td>0.86</td>
</tr>
<tr>
<td>1 year old</td>
<td>4 years old</td>
<td>0.84</td>
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<tr>
<td>1 year old</td>
<td>5 years old</td>
<td>0.93</td>
</tr>
<tr>
<td>1 year old</td>
<td>6 years old</td>
<td>0.84</td>
</tr>
</tbody>
</table>

Table 5: The table shows the true-positive rates when forming pairs of children at specific ages to investigate the robustness of age-invariant verification. While the true-positive rate is generally higher for smaller age gaps, our approach still performs well when we use children at the age of 1 and children at the age of 6 yielding a true-positive rate of 84%.

6. Conclusions

In this paper, we investigated how the task of age-invariant infant face verification can be solved using adapted DeepID2 features [SCWT14] combined with popular classification network architectures. In contrast to previous work focusing on the creation of age-invariant feature extraction or generation, we showed that classic deep feature descriptors can be adapted for age-invariant infant verification when trained on an appropriate dataset. We focused on children faces whose features change drastically in the early years as these are especially challenging for the face verification task. Since no existing dataset provided enough infant face images to train a CNN, we first prepared a dataset consisting of 4,528 face images of 42 children in age range of 0 to 6 years. Therefore, our dataset entails a vast number of examples for facial features changing due to aging effects in the early childhood.

We tested classification networks based on Residual Units [HZRS16] and Inception Modules [SL15] as both architectures have shown outstanding performance at classification tasks. For both tests, we first used adapted DeepID2 features in two branches as proposed by Siamese networks to extract two feature matrices from two presented input images. Afterwards the difference of the features is computed and passed to the classification part of the network. The classification network produces a probability as output which indicates whether the two input images show the same child or not. We train both of our combined networks end-to-end on the train subset of our dataset, achieving an accuracy of 85. Both network combinations showed promising results on our test dataset and on the infant subset of the FGNET [Ign] dataset. For our test dataset, we achieve the best accuracy (85.3%) with the Inception Modules network, slightly outperforming the Residual Units network (84.1% accuracy). Overall, the proposed network outperforms previous work when applied to the children subset of the FGNET database containing children from 0 to 4 years. The combinations of our adapted DeepID2 features with a classifier based on Inception Modules achieves an accuracy of 72.6% on this subset. In the future, we intend to investigate face verification of older children and will evaluate the possibilities of making our infant dataset available for future research.

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References


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