Gait-based Age Estimation using a DenseNet*

Atsuya Sakata[1], Yasushi Makihara[1], Noriko Takemura[1], Daigo Muramatsu[1], and Yasushi Yagi[1]

Osaka University, Japan {sakata, makihara, muramatsu, yagi}@am.sanken.osaka-u.ac.jp, takemura@ids.osaka-u.ac.jp

Abstract. Human age is one of important attributes for many potential applications such as digital signage, customer analysis, and gait-based age estimation is promising particularly for surveillance scenarios since it can be available at a distance from a camera. We therefore proposed a method of gait-based age estimation using a deep learning framework to advance the state-of-the-art accuracy. Specifically, we employed DenseNet as one of state-of-the-art network architectures. While the previous method of gait-based age estimation using a deep learning framework was evaluated only with a small-scale gait database, we evaluated the proposed method with OULP-Age, the world's largest gait database comprising more than 60,000 subjects with age range from 2 to 90 years old. Consequently, we demonstrated that the proposed method outperform existing methods based on both conventional machine learning frameworks for gait-based age estimation and a deep learning framework for gait gait recognition.

Keywords: Gait · Age · DenseNet.

1 Introduction

Image-based human age estimation has recently become an attractive research topic in computer vision, pattern recognition, and biometrics, since there are many potential applications. For example, once a target person's age is estimated, an advertiser can change a content of a digital signage into more suitable one for the estimated age, and a shop manager may arrange goods based on customer's age statistics. It is also possible to prevent that people under age buy alcohol or cigarette based on the estimated age.

Most of the image-based human age estimation relies on facial image analysis [1–4] as we human also do so. In addition to the facial image analysis, gait video analysis for age estimation is promising, since it does not require as high image resolutions as the facial image analysis. Therefore, it can be available even at a distance from a camera without subject cooperation [5, 6], and which makes it much wider an application range of the image-based human age estimation, e.g., getting customer's age statistics from a wider area than a shop (e.g., the whole shopping mall), finding a lost child in a shopping mall, finding suspect candidates based on witness about his/her age.

In the early stage, research on gait-based age analysis started with age group classification such as classification of children and adults using representation of point light

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sources attached to some body joints [7], or classification of the younger and the elderly using minimum foot clearance from the ground [8]. Subsequently, an image analysis-based approach to classification of children, adults, and the elderly has been proposed in [9]. Thereafter, studies on gait-based age estimation has been started since 2010, by using an appearance-based gait feature such as gait energy image (GEI) [10] (a.k.a. averaged silhouette [11]), frequency-domain feature [12], or depth gradient histogram energy image (DGHEI) [13] in conjunction with machine learning techniques, for example, multi-label guided (MLG) subspace learning [14], ordinary preserving manifold learning [15], Gaussian process regression [16], ordinary preserving linear discriminant analysis (OPLDA) and ordinary preserving margin Fisher analysis (OPMFA) [17], support vector regression (SVR) [18], and age group-dependent manifold learning and regression [19].

In addition to the above-mentioned conventional machine learning-based approaches, Marin-Jimenez et al. [20] proposed a deep learning-based gait-based age estimation. More specifically, the authors design a multi-task deep model which outputs age as well as identity and gender. The model is, however, trained and tested only with small-scale gait database, i.e., TUM-GAID [21], which composed of 305 subjects almost in their twenties. Since a deep learning-based approach generally requires a huge number of training samples to reach a satisfactory accuracy, and also reasonable evaluation of gait-based age estimation requires a wide age range, we would say that the method [20] is not fully validated.

We therefore want to validate a deep learning-based approach to gait-based age estimation in this paper. Specifically, we designs a model for gait-based age estimation based on DenseNet [22], a state-of-the-art network architecture so far, and also train and test the model using the world largest gait database, OULP-Age [18], which comprising over 60,000 subjects with wide age range.

2 Proposed method

2.1 Input data

As appearance-based gait features [10–12, 23, 24] are more often used than the model-based gait features [25, 26] in the gait recognition community. In particular, silhouette-based representation is dominant in the gait recognition community, since it can avoid being affected by clothes colors and textures, unlike the person re-identification task. We therefore adopt GEI [10] as the most widely used silhouette-based gait representation as input data for our deep learning model. We set the GEI size as 88 by 128 pixels.

2.2 Network structure

We employ DenseNet [22] as a state-of-the-art network structure for our gait-based age estimation task. While the residual network (ResNet) [27] exploits a skip connection from a single previous layer, DenseNet exploits skip connections from all the preceding layers as shown in Fig. 1. DenseNet achieves the state-of-the-art accuracies with less

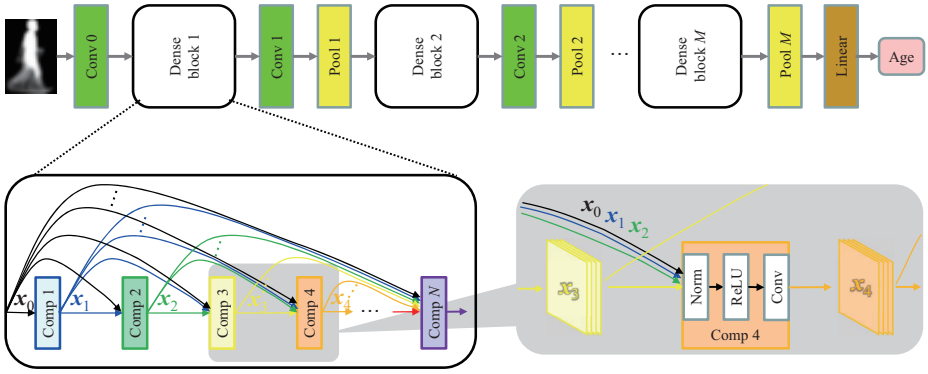


Fig. 1. An illustration of network architecture with M dense blocks, M composite layers, and growth rate $k = 4$.

parameters thanks to the dense connectivity, on object classification tasks as well as other tasks such as optical flow estimation [28] and saliency map estimation [29]. We briefly describe the network structure below and may refer the readers to [22] for more details.

DenseNet is mainly composed of multiple dense blocks and in-between transition layers including a pair of 1×1 convolution layer and a 2×2 average pooling layer with stride 2. Each dense block is then composed of multiple composite layers with dense connection, where each composite layer comprises a triplet of a 1×1 batch normalization layer, a rectified linear unit (ReLU) [30], and a 3×3 convolution layer. Here, we consider M dense blocks, and each dense block is composed of N composite layers. Given an input $\boldsymbol{x}_0$ to a dense block whose number of feature maps is k_0, it is fed into the following composite layers (i.e., Comp 1, Comp 2, ..., Comp N) as shown in Fig. 1. The l-th composite layer receives feature maps from all the preceding composite layers, i.e., $[\boldsymbol{x}_0, \boldsymbol{x}_1, \ldots, \boldsymbol{x}_{l-1}]$, and then output $\boldsymbol{x}_l$ whoes number of feature maps is k, which is so-called growth rate. In summary, the number of feature maps which the l-th composite layer receives, sums up to $k_0 + k(l-1)$, and hence each composite layer enjoys a sort of collective knowledge from the preceding layers. Specifically, we experimentally used $M = 5$ dense blocks and each dense blocks has $N = 5$ composite layers with $k = 12$ growth rate.

In addition to the above-mentioned main part, we insert a 7×7 convolution layer with stride 2 (Conv 0) before the first dense block, and also a 7×7 global average pooling layer followed by a one-dimensional full connection layer to output an age.

3 Experiments

3.1 Data set

We employed OULP-Age [18] as the world's largest gait database for gait-based age estimation. OULP-Age was collected in conjunction with long-run exhibition of experience-

based gait analysis demo in a science museum for an approx one year [31]. It consists of 63,846 (31,093 males and 32,753 females) with age ranging from 2 to 90 years old. The database is divided into a training set composed of 31,923 subjects (15,596 males and 16,327 females) and a test set composed of 31,923 subjects (15,497 males and 16,426 females).

3.2 Training

The network was trained using stochastic gradient descent (SGD) [32] with batch size 64 and 100 epochs. An initial learning rate was set to 0.1 and divided by 10 at epoch 50 and 75. We use a Nesterof momentum [33] of 0.9 without dampening. We adopt the weight initialization introduced by He et al. [34]. A loss function was set to sum of absolute difference between an output (i.e., estimated) age and the ground truth age.

3.3 Evaluation measure

We evaluated the accuracy of gait-based age estimation using a mean absolute error (MAE). MAE is computed by comparing the estimated age $\hat{a}_i$ for the i-th test sample with its corresponding ground truth age a_i as

$$M = \frac{1}{n}\sum_{i=1}^{n}|\hat{a}_i - a_i|, \tag{1}$$

where n is the number of the test samples. In addition, we employed a cumulative score (CS) for evaluating gait-based age estimation. Specifically, we define the number of test samples whose absolute difference between an estimated age and the ground truth age is less than or equal to y as $n(y)$, and then CS of the y-year absolute error as

$$\mathrm{CS}(y) = \frac{n(y)}{n}. \tag{2}$$

3.4 Sensitivity analysis

Since the number of blocks M and the number of composite layers N are two key hyper-parameters for DenseNet, we analyze the sensitivity of these two hyper-parameters on gait-based age estimation accuracy. Specifically, we set $M \in \{2, 3, 4, 5, 6, 7\}$ and $N \in \{4, 5, 6\}$ and then evaluate an MAE for each parameter combination as shown in Fig. 2. As result, we can see that the number of dense blocks has an impact on the accuracy, namely, the accuracy significantly drop if the number of dense blocks is less than 5. On the other hand, the number of composite layers does not have much impact on the accuracy, at least within the range from 4 to 6.

3.5 Comparison with state-of-the-arts

Finally, we compared the proposed method with benchmarks. As a baseline algorithm, a method using GPR with radial basis function [16] was adopted. More specifically, it

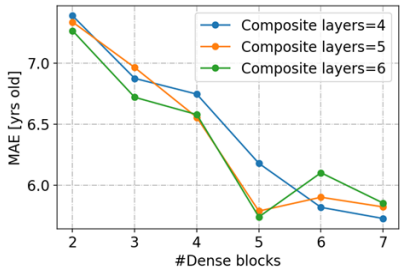


Fig. 2. Sensitivity analysis of the number of dense blocks and composite layers on MAE.

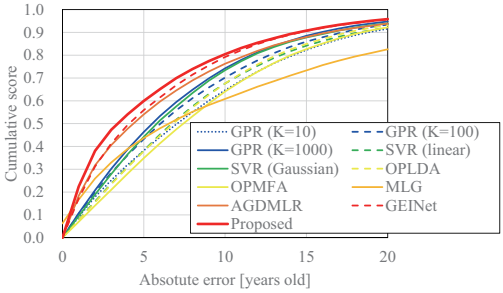


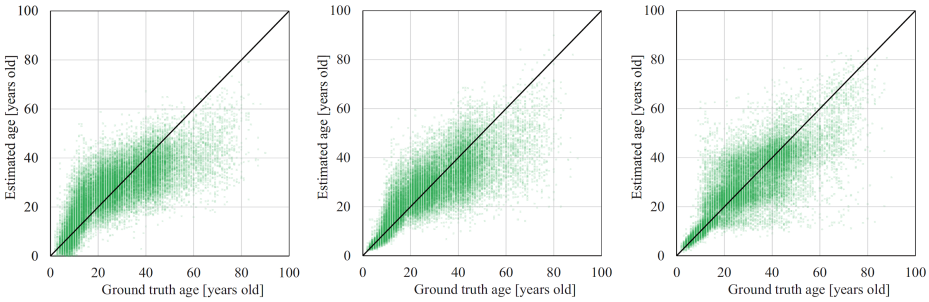
Fig. 3. Cumulative score.

Table 1. MAE [%] and cumulative score at 1, 5, and 10 years absolute errors. Bold and italic bold indicate the best and the second best performances, respectively.

Method	MAE	CS(1) [%]	CS(5) [%]	CS(10) [%]
MLG [14]	10.98	16.7	43.4	60.8
GPR ($k = 10$) [16]	8.83	9.1	38.5	64.7
GPR ($k = 100$) [16]	7.94	10.5	43.3	70.2
GPR ($k = 1000$) [16]	7.30	10.7	46.3	74.2
SVR (linear)	8.73	7.9	38.2	67.6
SVR (Gaussian)	7.66	9.4	44.2	73.4
OPLDA [17]	8.45	7.7	37.9	67.6
OPMFA [17]	9.08	7.0	34.9	64.1
ADGMLR [19]	6.78	***18.4***	54.0	76.2
GEINet [35]	***6.22***	17.2	***55.9***	***79.2***
Proposed method	**5.79**	**22.5**	**55.9**	**80.4**

requires huge computation on a gram matrix and its inverse matrix if all the training samples are used, we employ an active set method in the same way as in [31], where k nearest neighbors for each test sample are used for GPR and $k = 10, 100, 1000$ were evaluated. We also tested support vector regression (SVR) with linear and Gaussian kernels, denoted as SVR (linear) and SVR (Gaussian). We also evaluated existing methods of gait-based age estimation using conventional machine learning techniques such as MLG [14], OPLDA [17], OPMFA [17], and AGDMLR [19]. In addition, we employed a slightly modified version of GEINet [35] as a deep learning-based approach to age estimation. More specifically, the original GEINet outputs class (i.e., subject) likelihoods and hence the number of nodes at the last layer is equal to the number of subjects. On the other hand, the modified version of GEINet outputs an age and hence the last layer has just a single node.

CSs for the benchmarks and the proposed method are shown in Fig. 3. Also, MAEs and CSs for 1, 5, and 10 years tolerance are summarized in Table 1. As a result, deep learning-based methods (i.e., GEINet [35] and the proposed method) significantly out-



(a) GPR ($k = 1000$) [16] (b) GEINet [35] (c) Proposed method

Fig. 4. Scatter plot between ground truth age and estimated age. Diagonal lines show equal lines of ground truth age and estimated age.

perform the other methods without deep learning. In addition, the proposed method outperforms GEINet. This is because the proposed method exploit more collective information by dense connectivity while a basic structure of GEINet is derived from AlexNet [36] without such a dense connectivity.

Moreover, scatter plots between the ground truth age and the estimated ages are shown for the baseline GPR ($k = 100$) as a non-deep learning-based method [16], GEINet [35] as a deep learning-based method, and the proposed method in Fig. 4. While the estimated ages for the baseline algorithm (Fig. 4 (a)) is largely deviated for all the age range, GEINet (Fig. 4 (b)) suppressed such a deviation, particularly, for the children under 15 years old. The proposed method further suppress the deviation for the children and then yielded the best accuracy as a result.

4 Conclusions

In this paper, we proposed a method of gait-based age estimation using a deep learning framework. Specifically, we employed DenseNet as a state-of-the-art network architecture for gait-based age estimation, and demonstrated its effectiveness with OULP-Age, the world's largest gait database comprising more than 60,000 subjects with age range from 2 to 90 years old.

One of future research avenues is further investigating suitable network architectures for gait-based age estimation, e.g., ResNet [27], PyramidNet [37], and ShakeNet [38]. In addition, it is also worth investigating multi-task learning framework, e.g., [20].

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