

# Gait-based Age Estimation using a Whole-generation Gait Database

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## Abstract

*This paper addresses gait-based age estimation using a large-scale whole-generation gait database. Previous work on gait-based age estimation evaluated their methods using databases that included only 170 subjects at most with a limited age variation, which was insufficient to statistically demonstrate the possibility of gait-based age estimation. Therefore, we first constructed a much larger whole-generation gait database which includes 1,728 subjects with ages ranging from 2 to 94 years. We then provided a baseline algorithm for gait-based age estimation implemented by Gaussian process regression, which has achieved successes in the face-based age estimation field, in conjunction with silhouette-based gait features such as an averaged silhouette (or Gait Energy Image) which has been used extensively in many gait recognition algorithms. Finally, experiments using the whole-generation gait database demonstrated the viability of gait-based age estimation.*

## 1. Introduction

Recently, biometrics has increasingly attracted attention as a key technology for realizing a more secure and safer society. Although most of the studies on biometrics focus on person authentication or identification, namely *hard biometrics*, it is also important to promote the recognition of properties such as gender, age, and ethnicity, namely *soft biometrics*. Face-based age estimation has already been installed in adult authentication systems for automatic vending machines of cigarettes in several countries. In addition, there are many other potential applications such as automatic customer counting by gender and age group for marketing research.

Among biometric modalities, gait has several promising properties such as availability at a distance from a camera even without the cooperation of the subject; hence gait-based hard biometrics [28][31][27][11][23] has been extensively studied over the last decade with the aim of realizing wide-area surveillance and assistance with criminal investigation.

Furthermore, gait-based soft biometrics are also

an active research area (e.g., gender classification [14][17][12][2][18][38], age group classification [4][1][24], age estimation [21][20], and ethnicity classification [21]). In particular, gait-based age estimation is one of the challenging but encouraging areas of research motivated by several applications such as detection of lost children in shopping malls and wandering elderly in care homes.

On the other hand, large-scale gait databases are essential for statistically reliable evaluation of gait-based age estimation. Although several gait databases have been proposed and some are available (e.g., USF dataset [31], Soton (Southampton) [26][25], CASIA dataset [36], and OU-ISIR Gait Database [30]), they include only 170 subjects at most and contain significant biases in terms of gender and age (e.g. the majority are males in their twenties). The only exception is the large-scale gait database proposed in [29], which includes 1,035 subjects (569 males and 466 females) with ages ranging from 2 to 94 years. The large-scale gait database, however, still suffer from a shortage of subjects in several age ranges such as 15 to 19 years and over 50 years, which are important for age estimation.

Therefore, we constructed a larger whole-generation gait database including 1,728 subjects initially with fewer age biases than [29]. We then provided a baseline algorithm for gait-based age estimation using Gaussian process regression [3] which has been adopted by state-of-the-art algorithms for face-based age estimation [39]. This was in conjunction with silhouette-based gait features such as averaged silhouettes (or Gait Energy Images) [19][11] which have also been used in many other gait recognition studies [2][37][33][22]. Finally, we investigated the possibility of gait-based age estimation using the constructed whole-generation gait database.

The remainder of this paper is organized as follows. Section 2 briefly reviews related work on face-based and gait-based age group classification and age estimation. Section 3 describes our whole-generation gait database and subsequently Section 4 describes a baseline algorithm for gait-based age estimation using Gaussian process regression. Section 5 presents experiments of gait-based age estimation using the whole-generation gait database and Section 6 pro-

vides a discussion based on examples of success and failure modes. Finally, Section 7 concludes this paper and suggests future research on the subject.

## 2. Related work

### 2.1. Face-based age estimation

The face based age group classification problem is usually defined as a multi-class classification problem and is solved by using several classifiers such as a nearest neighbor classifier and a neural network classifier [15].

Face-based age estimation is formulated as a regression problem from face features to age, and estimation approaches mainly fall into two groups: global model based approaches and personal model based approaches.

The global model based approaches assume the common aging process and hence apply the same regression model using a quartic function [16], a kernel function [35], support vector regression [10], Gaussian Process Regression (GPR) [3], and Warped Gaussian Process Regression (WGPR) [32]. Manifolds parameterized by ages are also regarded as types of regression models, and hence manifold learning and metrics learning techniques are introduced to face-based age estimation in [5][9][34].

The personal model based approaches assume that aging processes differ between people and hence apply person-specific models defined as linear regression [8], nonlinear regression [7], and multi-linear regression from a tensor with missing data [6]. Zhang et al. [39] regarded a personal age estimation problem as one of multiple tasks and introduced Multi-Task Warped Gaussian Process Regression (MTWGPR).

Although in general personal model-based approaches achieved better performance than global model-based approaches, they essentially need multiple-age training samples for each target person, which are unavailable when the target is the general public.

### 2.2. Gait-based age estimation

For gait-based age group classification, Daves et al. [4] classified children (3-5 years old) and adults (30-52 years old), and Begg et al. [1] classified younger people (average: 28.4 years old, standard deviation: 6.4 years) and the elderly (average: 69.2 years old, standard deviation: 5.1 years). Mannami et al. [24] classified four groups: children (under 15 years old), adult male, adult female, and the elderly (over 65 years old) using the OU-ISIR Gait Database [30].

For gait-based age estimation, Lu et al. proposed a learning method of an age-ordinary preserving discriminant subspace [21] and a multi-label guided subspace [20].

As seen from the above, there are far fewer studies on gait-based age group classification and age estimation than face-based studies. This is because the existing gait databases were inadequate in terms of age variation and

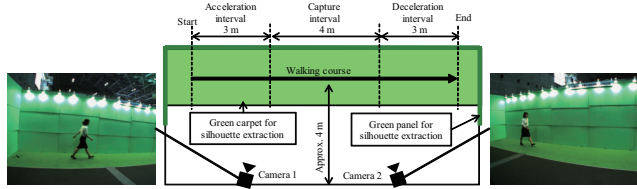


Figure 1. Gait measurement system and captured image samples.

the number of subjects, while the existing face databases (e.g., MORPH database [13]) contain sufficient age variation and subjects. Therefore, one of the important contributions of this paper is to construct the first whole-generation gait database with sufficient subjects for evaluating the performance of gait-based age group classification and age estimation.

## 3. Whole-generation gait database

### 3.1. Gait measurement system

In this section, our measurement system for creating the gait database is presented. First, a 10 m walking course was prepared and each subject was asked to walk at his or her own preferred speed along the course as shown in Fig. 1. Because gait tends to be unstable during acceleration and deceleration intervals at the beginning and end, a 4 m intermediate capturing interval was used for the observation.

Two cameras were then set up at approximately 4 m from the walking course to observe (1) the transition from a side view to a rear-oblique view and (2) the transition from a front-oblique view to a side view. The camera used was Flea2 by Point Grey Research Inc, and the image size and frame-rate were VGA ( $640 \times 480$  pixel) and 30 fps.

In addition, green background panels and carpets were arranged along the walking course for the purpose of clear silhouette extraction. Examples of the captured images are shown in Fig. 1.

### 3.2. Data collection and statistics

The data collection process and resultant subject statistics are described in this section. The dataset was collected in conjunction with an entertainment-oriented demonstration of gait personality measurement in three events like an outreach activity of a research project, an exhibition of surveillance technologies, and an open campus day. Each subject was asked to sign a release agreement to permit the use of the data for research purposes.

As a result of the data collection, we have constructed the world’s largest gait database including 1,728 subjects (1,007 males and 721 females) with ages ranging from 2 to 94 years old. Details of subject statistics in terms of gender and age groups in 5 year intervals are shown in Fig. 2. Compared with existing gait databases the following are the three main strengths of our gait database.

1. **Whole generation:** The age range of our gait database

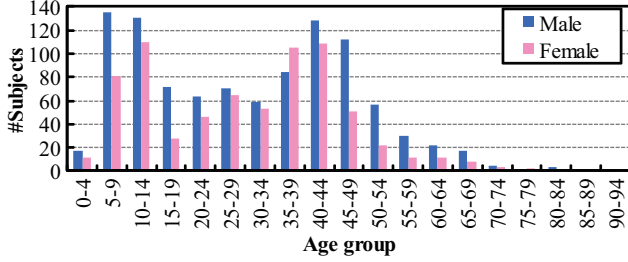


Figure 2. Statistics of subjects' gender and age.

is from 2 to 94 years old and each age group in 5-year intervals from 5 to 49 years old contains more than 100 subjects. In addition, it is particularly notable that our gait database includes sufficient children in the process of growing where other large-scale gait databases are mainly composed of adult subjects. Naturally, these properties are directly beneficial to gait-based age estimation in terms not only of performance evaluation but also reliable regression model training.

- Large population:** The number of subjects is approximately 10 times the number in existing large-scale gait databases [24]. This significantly improves the statistical reliability of the performance evaluation of gait-based age estimation.
- Gender balance:** The ratio of male to female is approximate 10 to 7, and it is less biased compared with the existing large-scale gait databases (e.g. the ratio of male to female in CASIA dataset [36] is approximately 3 to 1). This enables an investigation of the gender impact on gait-based age estimation performance and also the construction of gender dependent gait aging models or regression models for further research.

## 4. Gait-based age estimation

### 4.1. Gaussian process regression

Because Gaussian Process Regression (GPR) [3] has been adopted as the state-of-the-art method in face-based age estimation [39], it is also incorporated in our gait age estimation solution.

The Gaussian process is organized mainly in two steps as shown in Fig. 3. In the first step, the Gaussian distribution of the regressand age  $f$  is derived from the regressor gait feature  $\mathbf{x}$  and the regression parameter  $\Theta$ . In the second step, the Gaussian distribution of the observed age  $y$  is derived from that of the regressand age  $f$  and the observation noise  $\sigma$ .

Next, let us assume that a training set  $D = [X, \mathbf{y}]$  is given, where  $X = [\mathbf{x}_1, \dots, \mathbf{x}_N]$  is a set of  $N$  samples of gait features and  $\mathbf{y} = [y_1, \dots, y_N]$  is a set of the corresponding ground truth ages. Then, given a new gait feature

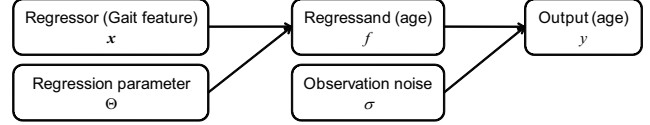


Figure 3. Diagram of GPR

$\mathbf{x}_*$ , GPR tries to estimate a distribution of an age  $y_*$  for the gait feature  $\mathbf{x}_*$  based on the training set  $D$ .

In order to treat non-linear regression, mapping  $\phi$  from a gait feature  $\mathbf{x}$  to a higher-dimensional feature space is introduced with the parameter  $\Theta$  as  $\phi(\mathbf{x}; \Theta)$ . Then, a regressand age  $f$  is given by linear regression in the higher-dimensional feature space as

$$f(\mathbf{x}; \Theta) = \phi(\mathbf{x}; \Theta)^T \mathbf{w}, \quad (1)$$

where  $\mathbf{w}$  is a vector of linear regression coefficients in the higher-dimensional feature space. Moreover, the mapping of  $\phi$  is implicitly defined by the so-called kernel trick and hence an inner product in the higher-dimensional feature space  $k(\mathbf{x}_i, \mathbf{x}_j; \Theta) = \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)$  is defined as Gaussian kernel like

$$k(\mathbf{x}_i, \mathbf{x}_j; \Theta) = v \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|}{2r^2}\right) \quad (2)$$

where  $\Theta = [v, r]^T$  is a parameter vector for the Gaussian kernel.

Consequently, a posterior probability distribution  $P(f|\mathbf{x}_*, D)$  of a regressand age  $f$  is defined as a Gaussian distribution  $\mathcal{N}(\mu_f, \sigma_f^2)$  [3]. Here, mean  $\mu_f$  and variance  $\sigma_f^2$  are defined as

$$\mu_f = \mathbf{k}_*^T (K + S)^{-1} \mathbf{y} \quad (3)$$

$$\sigma_f^2 = k(\mathbf{x}_*, \mathbf{x}_*) - \mathbf{k}_*^T (K + S)^{-1} \mathbf{k}_*, \quad (4)$$

where  $K$  is a  $N \times N$  square matrix whose  $(i, j)$  component is  $k(\mathbf{x}_i, \mathbf{x}_j)$ ,  $\mathbf{k}_*$  is an  $N$ -dimensional vector and the whole  $i$ th row is  $k(\mathbf{x}_i, \mathbf{x}_*)$ ,  $S$  is a  $N \times N$  diagonal matrix whose  $(i, i)$  component is  $\sigma^2$ , namely, the observation noise variance.

Finally, a posterior probability distribution  $P(y|\mathbf{x}_*, D)$  of an output age  $y$  is also defined as a Gaussian distribution  $\mathcal{N}(\mu_y, \sigma_y^2)$ , where

$$\mu_y = \mu_f \quad (5)$$

$$\sigma_y^2 = \sigma_f^2 + \sigma^2. \quad (6)$$

### 4.2. Parameter learning

Because the Gaussian kernel parameter  $\Theta$  and the observation noise  $\sigma$  used in GPR are unknown parameters, they need to be learnt with the training set  $D = [X, \mathbf{y}]$ . Specifically, they are estimated by maximizing a likelihood of out-



Figure 4. Examples of frequency-domain features [23]. Left, middle, and right images for each subject are the direct currency elements (averaged silhouettes), one-time frequency elements, and two-time frequency elements of amplitude spectra when the gait period is used as the base period for Fourier analysis.

put ages  $\mathbf{y}$  under the observation of gait features  $X$  as

$$P(\mathbf{y}|X) = \int P(\mathbf{y}|\mathbf{f})P(\mathbf{f}|X)d\mathbf{f} \\ = \frac{1}{(2\pi)^{\frac{N}{2}}|K+S|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}\mathbf{y}^T(K+S)^{-1}\mathbf{y}\right) \quad (7)$$

Note that the Gaussian kernel parameter  $\Theta$  and observation noise  $\sigma$  are included in matrices  $K$  and  $S$ , respectively.

On the other hand, it is well known that the maximization of the following log likelihood  $l = \log P(\mathbf{y}|X)$  is better than that of the original likelihood in terms of stability in numerical computation.

$$l = -\frac{1}{2}\mathbf{y}^T(K+S)^{-1}\mathbf{y} - \frac{1}{2}\log|K+S| - \frac{N}{2}\log\pi \quad (8)$$

Finally, the parameters  $\Theta$  and  $\sigma$  are optimized by maximizing the log likelihood with a conjugate gradient method.

## 5. Experiments

### 5.1. Method

Gait-based age estimation based on GPR was evaluated using the whole-generation gait database. Approximately half the subjects for each generation were chosen as training samples, which added up to 877 subjects, while the other 851 subjects were used as test samples.

Gait features as a regressor contain three silhouette-based features: (1) the averaged silhouettes or Gait Energy Images [19][11] (denoted GEI later), which have been the most widely used, (2) the frequency-domain features [23] (denoted FREQ later), which include not only the averaged silhouettes (direct currency elements) but also one and two-times the frequency elements shown in Fig. 4, and (3) the gait periods (denoted by GP later) detected by maximizing the normalized autocorrelations [23]. The performance of gait-based age estimation is measured by a Mean Absolute Error (MAE) and a cumulative score. Given the estimated age  $\hat{y}_i^t$  and ground truth age  $y_i^t$  for the  $i$ th test sample, the MAE  $E$  between them is defined as

$$E = \frac{1}{N^t} \sum_{i=1}^{N^t} |\hat{y}_i^t - y_i^t|, \quad (9)$$

where  $N^t$  is the number of test samples. In addition, the cumulative score for  $l$  years absolute error tolerance  $S(l)$  is

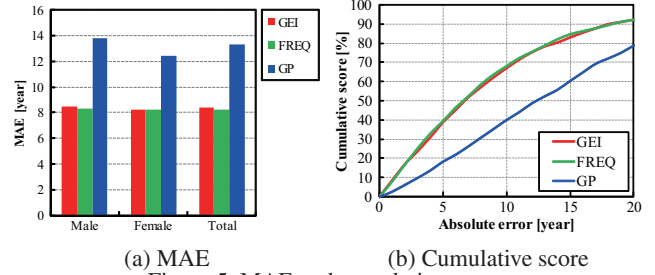


Figure 5. MAE and cumulative score.

defined as the ratio of the number of subjects within  $l$  years absolute error  $N^t(l)$  to that of all the test samples  $N^t$  as

$$S(l) = \frac{N^t(l)}{N^t}. \quad (10)$$

## 5.2. Results

In this section, the performance of gait-based age estimation is evaluated by the MAE and the cumulative scores as shown in Fig. 5.

As a result, it emerged that FREQ achieves the best MAE (8.2 years) and also the best cumulative score (e.g. the absolute errors of 68% and 85% subjects are less than 10 and 15 years, respectively). GEI is slightly worse than FREQ, the difference is, however, insignificant. Moreover, although the MAE of females is better than that of males (e.g., 8.2% to 8.3% in FREQ), the impact of gender difference is still insignificant. On the other hand, the GP is much worse than the other two gait features. This is because gait periods and ages are almost uncorrelated when the subjects have grown up, although they are correlated during the growing period (e.g., from 0 to 15 years old).

## 6. Discussion

In this section, several success and failure modes of GEI are discussed based on Fig. 6.

First, we focus on the successful subjects within 3 years of absolute error. During the growth of a child (e.g. from 0 to 20 years old), we can observe clear changes in body shape such as ratio of head to full body. In addition, the relative stride to height tends to be large during childhood, in particular, for boys under 10 years of age. After growing up, while the arm swings of subjects in their twenties tend to be small, those in their thirties or older tend to be larger. On the other hand, when getting older (e.g. after 40 years of age), middle-age spread and stoop are observed in most of the subjects. Consequently, these kinds of correlations between gait features and ages enable gait-based age estimation.

Next, we focus on the failure modes. From our observation, the failures result mainly from two causes: (1) the difference between *gait age* and *actual age* and (2) the absence of training samples similar to a failed test sample.



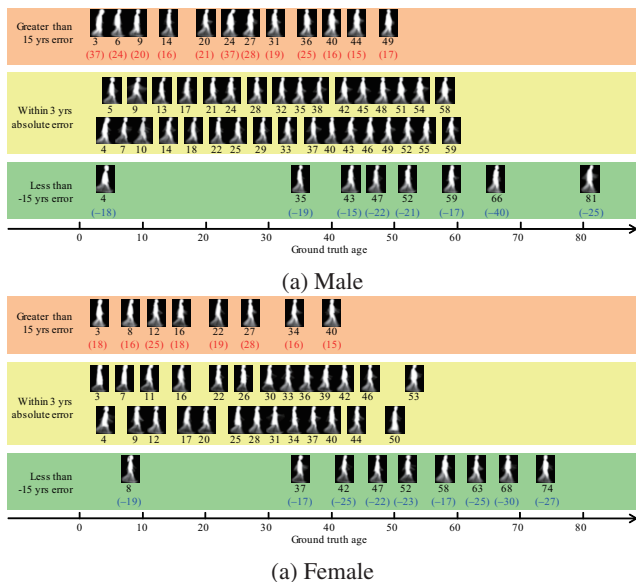


Figure 6. GEI grouped by age estimation errors: greater than 15 years (over-estimate failure), within 3 years (almost successful), and less than 15 years (under-estimate failure). Digits in black mean ground truth age, bracketed digits in red and blue mean over- and under-estimated age errors, respectively. Each subject is aligned along with the ground truth age by gender.

The first failure occurred when the gait features of failed subjects significantly deviated from the gaits of their actual ages. For example, it is observed that the middle-age spread and/or stoop of over-estimated male adults is much more apparent than in successfully estimated subjects of the same generation and hence their gait features look like those of middle-age adults or the elderly, and vice versa. These failure modes, however, suggest another interesting possibility that *gait age* estimation may be applied in the field of health science, medical science, and exercise science (e.g., *gait age* as a measure of physical strength and fitness promotion).

The second failure occurred when a test gait feature was very different from training gait features. For example, it was observed that some of the over-estimated boys had quite small forward steps, which is not seen in any of the successfully estimated subjects. These types of failures are common problems for a family of example-based regression approaches including the proposed baseline algorithm using Gaussian kernel-based regression. Therefore, we need further studies on sophisticated feature extraction such as part-based feature or decomposition of static (e.g., leg and arm lengths and body shape) and kinematic (e.g., joint angle sequences) features to solve this problem.

## 7. Conclusions

This paper described gait-based age estimation using a whole-generation gait database. The proposed gait database included 1,728 subjects with a wide age range (from 2 to 94

years old) and overcame shortcomings of the existing gait database in terms of age variation, the number of subjects, and gender balance. We also provided a baseline algorithm using Gaussian process regression and silhouette-based gait features. As a result of the experiments using the whole-generation gait database, the mean absolute error was 8.2 years for the frequency-domain features, which indicates a potential possibility for gait-based age estimation.

One important future study is the enhancement of the whole-generation gait database, particularly addition of the elderly. Moreover, there should be sufficient room for improvement from the baseline algorithm; hence, the other state-of-the-art gait features and/or regression methods will be incorporated while using the whole-generation gait database as a benchmark.

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