



Age Estimation using Kernel Regression Analysis

Hironobu Fukai[†], Hironori Takimoto[‡], Yasue Mitsukura* and Minoru Fukumi**

[†]Department of Media Technology, Ritsumeikan University
1-1-1 Nojihigashi, Kusatsu, Shiga, 525-0058 Japan
Email: fukai@fc.ritsumei.ac.jp

[‡]Department of Communication Engineering, Okayama Prefectural University
111 kuboki, souja-shi, 719-1197 okayama
Email: takimoto@c.oka-pu.ac.jp

* Graduate School of Bio-Applications & Systems Engineering, Tokyo University of Agriculture & Technology
2-24-16 Naka-cho, Koganei-shi, Tokyo, 184-8588 Japan
Email: mitsu_e@cc.tuat.ac.jp

** Institute of Technology and Science, The University of Tokushima
2-1 Minami-josanjima, Tokushima, 770 Japan
Email: fukumi@is.tokushima-u.ac.jp

Abstract—In this paper, we propose age estimation using kernel regression analysis. Age estimation is one of most difficult problem of facial recognition research areas. However, if age can be estimated by computer, it is possible to apply it to various fields, for example, marketing, communication person and machine, and so on. Then, there are many researches, but practical use research is few. Furthermore, a necessary technology changes greatly also under the environment respectively, for example, use ID photo, use images of takes before laptop PC, use images that takes surveillance camera. We focus on images from surveillance camera, and we aim to propose generalized age estimation method.

Therefore, we propose age estimation method using wrinkle and pigmented spot information that can be extract age feature invariably even if appearance changes. To extract pigmented spot and wrinkle information, we use ε -filter. Moreover, the kernel regression analysis is used for age estimation method. To evaluate effectiveness of the proposed, we simulate age estimation by using actual face image. As a result, age estimation error value is about 6.65 years old. This result is high accuracy as a generalized method.

1. INTRODUCTION

In our life, we estimate the person's age roughly by using our experience. Furthermore, we meet the person a lot in daily life and we can take a smooth and flexible response routinely by estimating age. For example, if we saw the elder person, we behave politely. Therefore, it is considered that age is one of the most important characteristics of a person. However, it is easy for us to estimate our age roughly, but it's difficult for the computer to do it. Therefore, age estimation methods based on images of face have been widely studied [1]-[10].

In a study on the change in the physical shape of the

face with age, Todd *et al.* [1, 2] indicate that the contour of the skull can be approximated by a cardioid transform. Yamaguchi *et al.* [3] confirm that the differences between the features of an adult's face and a child's face include the length of the face and the ratio of each part. Age estimation by computer has also been performed. Kanno *et al.* [4] show that a male can be identified by neural networks representing four ages (12 years, 15 years, 18 years, and 22 years). Kwon and Lobo [5] reported that the proposed method has been implemented to classify input images into one of three age-groups: babies, young adults, and senior adults by using the placement information and texture information. However, almost of all their studies were based on cranio-facial development method and skin wrinkle analysis. Burt and Perrett [6] studied age perception using averaged faces of people from 25 to 60 years old used a method of focusing on face texture and shape. Ueki *et al.* [7] reported a method of age-group classification by linear discriminant analysis (LDA). Takimoto *et al.* [8] proposed a gender and age estimation technique that is not influenced by posture changes by estimating a NN from several features including the face texture and features. We proposed novel age estimation system [9]. In this method, we reported that the proposed method can estimate the apparent-age and gender by frequency feature of a face. Recently, practicable method is proposed. Ihara *et al.* [10] report age estimation using covariate shift adaptation. It's robust for illumination variation. However, there are no method that is robust for face rotation and position.

Therefore, we propose an age estimation system that aims for practical use. To extract age feature, we use the ε -filter. Moreover, the age is estimated continuously by kernel regression analysis. For the purpose of showing the effectiveness of the proposed method, computer simulations are performed using the actual data.

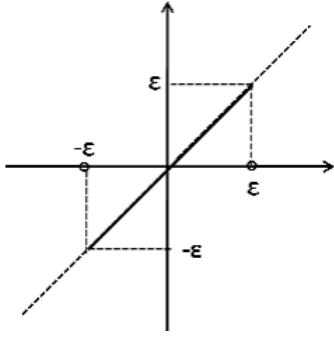


Figure 1: Example of nonlinear function

2. PROPOSED METHOD

In this section, we describe the procedure of the proposed method. The proposed method is constructed by 3 processings. The 1st processing is normalization of the facial image. The 2nd processing is age feature extraction. The 3rd processing is age estimation. We explain these 3 processings, respectively.

2.1. Normalization

It is necessary to normalize the face images for age estimation because the face area is different in facial image. Therefore, we detect facial area and skin area, and to normalize facial images.

2.2. Age Feature Extraction

It is known that the facial features are changed by aging. Especially, pigmented spot and skin wrinkle are well known.

2.2.1. Texture Feature

Pigmented spot and wrinkle on skin area are considered as minute change noise. Then, we use the ε -filter for extract this feature [11]. The ε -filter is defined as follows:

$$y(n) = x(n) + \sum_{k=-N}^N a_k F(x(n-k) - x(n)) \quad (1)$$

$$|F(x)| \leq \varepsilon : -\infty \leq x \leq \infty. \quad (2)$$

There is a difference of the I/O signal below ε when it is a nonlinear function that $F(x)$ shows in Fig.1. Example result of the ε -filter is shown in Fig.2. We subtract the result image of the ε -filter from original image and we make the histogram. Then, we normalize histogram by skin area. We adopt these histograms as texture features.

2.3. Age Estimation

We estimate age using kernel regression analysis. In this study, we estimate age using texture feature. Then,

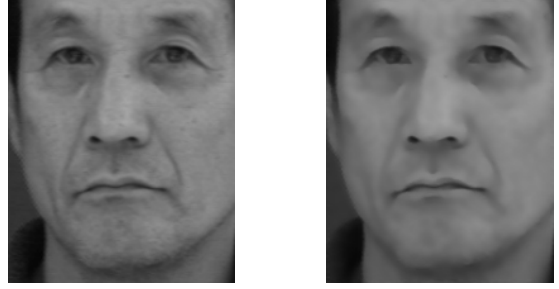


Figure 2: Result of ε -filter

age(AGE) are estimated by following equation.

$$AGE(x, w) = \sum_{n=1}^N w \phi(x_n) \quad (3)$$

where $\phi(x_n) = (\phi(x_1), \dots, \phi(x_D))^T$, and $\phi(x_n)$ are basis functions. Moreover, parameters w are determined by minimizing a regularized sum-of-squares error function given by

$$J(w) = \frac{1}{2} \sum_{n=0}^{N-1} \{w^T \phi(x_n) - t_n\}^2 + \frac{\lambda}{2} w^T w \quad (4)$$

λ means regularized parameter, and $\lambda \geq 0$. t_n is age values of training data sets. If we set the gradient of $J(w)$ equal to zero, w is

$$w = -\frac{1}{\lambda} \sum_{n=1}^N \{w^T \phi(x_n) - t_n\} \phi(x_n) = \sum_{n=1}^N a_n \phi(x_n) = \Phi^T a \quad (5)$$

If we substitute $w = \Phi^T a$ into $J(w)$, we obtain

$$J(a) = \frac{1}{2} a^T \Phi \Phi^T \Phi \Phi^T a - a^T \Phi \Phi^T \frac{1}{2} t^T t + \frac{\lambda}{2} a^T \Phi \Phi^T a \quad (6)$$

where $t = (t_1, \dots, t_N)^T$. If we define the Gram matrix $K = \Phi \Phi^T$, and $k_n(x) = \phi(x_n^T x)$, $J(w)$ is

$$J(a) = \frac{1}{2} a^T K K a - a^T K t \frac{1}{2} t^T t + \frac{\lambda}{2} a^T K a. \quad (7)$$

Then, we obtain

$$a = (K + \lambda I_N)^{-1} t. \quad (8)$$

Finally, we obtain the following prediction for a new input x

$$AGE(x) = w \phi(x) = a^T \Phi \phi(x) = k(x)^T (K + \lambda I_N)^{-1} t. \quad (9)$$

Furthermore, we use liner kernel, Gaussian kernel and polynomial kernel.

3. COMPUTER SIMULATIONS

3.1. Face Image Database

The face database was provided from the Human and Object Interaction Processing (HOIP) organization in

Table 1: Detail of the face image database

Size	640×480[pix.]
	24 bit color
Gender	150 images for each
Age	30 images per 5 years
Emotion	neutral
Rotation	H-45 ~ +45, V-15 ~ +15



Figure 3: HOIP database image

Japan [12]. The subject images comprised people with a wide range of ages. The background was made the same for all subjects. Furthermore, facial expression is neutral. Moreover, there are facial images of which it takes a picture from various directions. In this paper, the face database was used with permission from Softopia corporation, Japan. It is prohibited to copy, to use, and to distribute the images without the authorization of the copyright holder.

3.2. Conditions of Age Estimation

In order to show the effectiveness of the proposed method, we perform a simulation. In this paper, we use the actual data that is provided from HOIP organization in JAPAN [12], and we use a sample size of only 113 males, and it is only frontal face image, no-glasses. This is a first step of evaluation of the proposed method. Moreover, we use the ε -filter that window size is 7×7 and ε value is 20. In this simulation, we use the leave-one-out cross-validation method.

3.3. Age Estimation Results and Discussions

Table 2,3,4 shows error average of estimated age. In addition, we show the age estimation error of each generation. Table 2 means result of liner kernel, Table 3 shows result of Gaussian kernel and Table 4 is result of polynomial kernel. From these results, age estimation error of 10's, 20's, and 60's are larger than all generation's average. Moreover, to compare 3 results, good result of average and generation's average is polynomial kernel result. As a result, age estimation error value is about 6.65 years old. This result is high accuracy as a generalized method.

4. CONCLUSIONS

In this paper, we proposed an age estimation system based on texture feature. Firstly, we detect the face area and skin area, and normalize face image. Next, age feature

Table 2: Age estimation error using liner kernel

All generations	6.85 years
10's	8.77 years
20's	6.37 years
30's	4.66 years
40's	5.9 years
50's	6.3 years
60's	10.32 years

Table 3: Age estimation error using Gaussian kernel

All generations	6.64 years
10's	8.6 years
20's	6.14 years
30's	5.03 years
40's	6.22 years
50's	5.21 years
60's	9.75 years

is extracted by ε -filter. Finally, age is estimated by kernel regression analysis. From result, age estimation error value is about 6.65 years old. It's good result of age estimation research area. However, there are no simulation of female and multi direction face image. It's necessary to show the effectiveness of the proposed method.

References

- [1] J. T. Todd, L. S. Mark, R. E. Shaw and J. B. Pittenger, "The perception of human growth," *Scientific American Perception*, Vol. 242, pp. 106-114, 1980.
- [2] L. S. Mark, J. B. Pittenger, H. Hines, C. Carello, R. E. shaw and J. T. Todd, "Wrinkling and head shape as coordinated sources of age-level information," *Perception & Psychophysics*, Vol. 27, pp. 117-124, 1980.
- [3] M. K. Yamaguchi, T. Kato, and S. Akamatsu, "Relationship between physical traits and subjective impressions of the face - Age and sex information," *IE-ICE Trans.*, Vol. J79-A, No. 2, pp. 279-287, 1996.

Table 4: Age estimation error using polynomial kernel

All generations	6.65 years
10's	8.6 years
20's	6.23 years
30's	4.89 years
40's	6.43 years
50's	5.76 years
60's	8.71 years

- [4] T. Kanno, M. Akiba, Y. Teramachi, H. Nagahashi and T. Agui, "Classification of age group based on facial images of young males by using neural networks," *IE-ICE Trans. Inf. Syst.*, Vol. E84-D, No. 8, pp. 1094-1101, 2001.
- [5] Y. H. Kwon and N. D. V. Lobo, "Age classification from facial images," *CVPR'94*, pp.762-767, Seattle, US, June 1994.
- [6] D. M. Burt and D. I. Perrett: Preception of age in adult caucasian male faces, "computer graphic manipulation of shape and colour information," *Perception*, Vol. 259, No. 1355, pp. 137-143, 1995.
- [7] K. Ueki, T. Hayashida, and T.Kobayashi, "Subspace-based age-group classification using facial images under various lighting conditions," *Proc. IEEE Int. Conf. on Automatic Face and Gesture Recognition*, pp. 43-48, 2006.
- [8] H. Takimoto, Y. Mitsukura, M. Fukumi and N. Akamatsu, "A robust gender and age estimation under varying facial pose," *IEEJ Trans.*, Vol. 127, No. 7, pp. 1022-1029, 2007.
- [9] H. Fukai, H. Takimoto, Y. Mitsukura, T. Tanaka, M. Fukumi, "Apparent-age Feature Extraction by Empirical Mode Decomposition," *Journal of Signal Processing*, Vol. 12, No. 6, pp. 457-463, 2008.
- [10] Y. Ihara, M. Sugiyama, K.Ueki, "Age Estimation using Convariate Shift Adaptation," *ViEW2009*, pp. 325-330, 2009.
- [11] H. Watabe, K. Arakawa, Y. Arakawa, "A Nonlinear Digital Filter for Beautifying Facial Images," *Journal of Thee Dimensional Images*, Vol. 13, No. 3, pp. 41-46, 2003.
- [12] <http://www.hoip.jp>