Future of Privacy Forum
Performance Considerations for Automated Age Verification

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If age is just a number, what is that number measuring?
Overview

- Age Verification
- Types of Age Measures
- Modalities of Age Verification
- Early Age Verification: pre–Deep Learning
- Performance Comparison of Commercial Age Verification Solutions
Why Automatic Age Verification?
Access Control
Digital Signage & eCommerce


Dr. Karl Ricanek Jr (Lapetus Solutions Inc)
Digital Signage & eCommerce

Source: Legal & General UK (Lapetus Solutions, Inc)

The power of a SELFIE.

What is SelfieQuote?

Protect your family's future in just a snap! Legal & General America recently launched an easy and engaging way to get a life insurance quote: simply submit a photo of yourself, otherwise known as a 'selfie', and let technology do the rest.

SelfieQuote provides a life insurance quote by estimating an individual's age, gender, and body mass index (BMI) using an individual's selfie photo.

Legal & General America is the first in the life insurance industry to roll out the selfie-quotting technology. This groundbreaking digital experiment, now in beta phase, is made possible through a partnership with Lapetus Solutions, Inc (L5B), the science and technology company that created the new facial analytics technology.

Tips when submitting a selfie:
- Ensure your face is well-lit
- Remove glasses
- Push hair away from your face
- Look straight at the camera
- Keep camera/phone at arm's length

Submit a selfie, get a quote for life insurance!
Types of Age Measures

• **Chronological Age**
  • the amount of time elapsed since an individual’s birth, typically expressed in terms of months and years. Also called *calendar age.*
  (Source: [https://dictionary.apa.org/chronological-age](https://dictionary.apa.org/chronological-age))

• **Perceived Age**
  • Qualitative measure of chronological age based on a set of observers. Observers can be humans or machines.

• **Biological Age**
  • Qualitative measure of the senescing rate as a function of chronological age. Is the person aging faster, slower, or the same as someone their chronological age.
Age Measures

- Perceived Age: Man on right is older
- Chronologically these men are equal at 70 years old.
- Biologically these men are vastly different. The man on the left can expect to much longer than the man on the right
Age Measures Identical Twins

- Perceived Age: Different
- Chronological Age: Same
- Biological Age: Severely Different
Automatic Age Verification Modalities
Age and Gender Classification from Ear Images

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Abstract—In this paper, we present a detailed analysis on extracting soft biometric traits, age and gender, from ear images. Although there have been a few previous work on gender classification using ear images, to the best of our knowledge, this study is the first work on age classification from ear images. In the study, we have utilized both geometric features and appearance-based features for ear representation. The utilized geometric features are based on eight anthropometric landmarks and consist of 14 distance measurements and two area calculations. The appearance-based methods employ deep convolutional neural networks for representation and classification. The well-known convolutional neural network models, namely, AlexNet, VGG-16, GoogLeNet, and SqueezeNet have been adopted for the study. They have been fine-tuned on a large-scale ear dataset that has been built from the profile and close-to-profile face images in the Multi-PIE face dataset. This way, we have performed a domain adaptation. The updated models have been fine-tuned once more on the small-scale target ear dataset, which contains only around 270 ear images for training. According to the experimental results, appearance-based methods have been found to be superior to the methods based on geometric features. We have achieved an accuracy of about 75% on the multi-domain ear images dataset for gender and age classification.
Gait-based age estimation using multi-stage convolutional neural network

Atsuya Sakata, Noriko Takemura & Yasushi Yagi

IPSJ Transactions on Computer Vision and Applications 11, Article number: 4 (2019) | Cite this article

1934 Accesses | Metrics

Abstract

Gait-based age estimation has been extensively studied for various applications because of its high practicality. In this paper, we propose a gait-based age estimation method using convolutional neural networks (CNNs). Because gait features vary depending on a subject’s attributes, i.e., gender and generation, we propose the following three CNN stages: (1) a CNN for gender estimation, (2) a CNN for age-group estimation, and (3) a CNN for age regression. We conducted experiments using a large population gait database and confirm that the proposed method outperforms state-of-the-art benchmarks.
Hand Image-Based Human Age Estimation using a Time Distributed CNN-GRU

October 2020

DOI: 10.1109/ICDABI51230.2020.9325667

Conference: 2020 International Conference on Data Analytics for Business and Industry: Way Towards a Sustainable Economy (ICDABI)

Project: Biometrics

Mohamed Ait Abderrahmane · Ibrahim Guelzim · Abdelkaher Ait Abdelouahad
Age Prediction from Iris Biometrics

December 2013
DOI: 10.1049/ic.2013.0258
Conference: 5th International Conference on Imaging for Crime Detection and Prevention

Meryem Erbilek · M. Fairhurst · Márjory Da Costa-Abreu
Soft Biometrics for Age Verification

- Soft biometrics uses the biometric signals to determine automatic age.

- Often uses age ranges instead of point estimates.

- 2011 face-based soft-biometrics was formalized into facial analytics.

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Early Approaches to Chronological Age Verification (2008 to 2012)

Multi-factor Statistical Learning via Active Appearance Models

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High Fidelity Synthetic Age Progression
Active Appearance Models in Age Space

Ages: 20 to 91
Age: 19.5
Est: 29.5
Cor: 24.4

Est: MAE 3.4 yrs
Cor: MAE 2.1 yrs

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Chronological Age Estimation
Example of Results (age 18-29)

True age: 19
Est. age: 18.88
Abs Error: 0.12

True age: 20
Est. age: 20.02
Abs Error: 0.02

True age: 22
Est. age: 22.09
Abs Error: 0.09

True age: 29
Est. age: 29.43
Abs Error: 0.43
Chronological Age Estimation
Example of Results (age 30-59)

True age: 34  
Est. age: 33.74  
Abs Error: 0.76

True age: 45  
Est. age: 45.76  
Abs Error: 0.76

True age: 47  
Est. age: 47.20  
Abs Error: 0.20

True age: 54  
Est. age: 53.86  
Abs Error: 0.14
Chronological Age Estimation
Example of Results (age 60-93)

- True age: 63
  - Est. age: 63.10
  - Abs Error: 0.10

- True age: 72
  - Est. age: 71.99
  - Abs Error: 0.00

- True age: 83
  - Est. age: 83.14
  - Abs Error: 0.14

- True age: 93
  - Est. age: 92.48
  - Abs Error: 0.52
Summary

• Pros
  • Data requirements are dramatically less than Deep Learning
  • Robust to gender and ethnicity
  • Model captures aging factors

• Cons
  • Trial and error to identify parameters in the larger face space
  • Performance impacted by:
    • pose variations
    • illumination
    • expression
Deep Machine Learning Age Performance

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Deep Machine Learning

- Deep learning attempts to mimic the human brain—albeit far from matching its ability—enabling systems to cluster data and make predictions with incredible accuracy.

Source: https://www.ibm.com/cloud/learn/deep-learning

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Deep Machine Learning

• Pros
  • incredible ability to extract meaning, patterns, from data
  • feature generation
  • feature abstraction
  • performance

• Cons
  • volumes of data required (100,000 to 1,000,000 data points)
  • can easily be biased
  • modes of sensitivity are not well understood; requires extensive sensitivity testing prior to deployment
Large Scale Comparison of three Commercial Age Verification Solutions
Evaluation Dataset

- MORPH is a large-scale data corpus comprised of images with metadata for gender and age. The dataset contains multiple images of a person across time.
- MORPH: https://uncw.edu/oic/tech/morph.html

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# Chronological Age Verification

n = 138,839

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Sightcorp is formerly Sighthound
## Age Verification by Race

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Example: Female 80 years old

Gender: Female
BMI: Normal (21.3)
Age: 72.5
Example: Female 80 years old
Example: Female 40 years old
Questions

Dr. Karl Ricanek Jr (Lapetus Solutions Inc)