MJPAS

MUSTANSIRIYAH JOURNAL OF PURE AND APPLIED SCIENCES

Journal homepage:
https://mjpas.uomustansiriyah.edu.iq/index.php/mjpas

RESEARCH ARTICLE – COMPUTER SCIENCE

The use of Kinect sensor for human age estimation: A review

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Article Info.

Article history:

Received
10 June 2024

Accepted
2 Septemper 2024

Publishing
30 Septemper 2025

Abstract

Abstract: An age estimation term refers to the procedure of expecting a human's consecutive age based on different factors or indicators. These factors could be physical features like the color of the hair, wrinkles, and the shape of the body. Also, could be a biological feature like DNA methylation or dental growth. The approaches or techniques used in age estimation could be as simple as visual opinion or more complex as analyzing diverse databases using machine learning methods and algorithms. The algorithms used features extracted from images captured using various technologies, one of these technologies is the Kinect sensor due to its ability to provide facial, skeleton, and body features. In this study, age estimation applications, human age features, database, approaches used for age estimation, Kinect sensor abilities, limitations, and improvements algorithms, are presented with the most related works, the final section is for the conclusions.

The official journal published by the College of Education at Mustansiriyah University

Keywords: Kinect sensor; Age estimation; Age detection, Age estimation methods; Kinect application.

1. Introduction

The use of technologies and their applications in the modern world is in progress due to life needs, in the biometrics and computer vision field, the age estimation for the human from the images is essential which is used in different fields in life. So many applications include age estimation in its work like, health monitoring, forensics, biometric identification, security, education, and gaming.

Estimating human age involved the attention of the researchers, but there are no standards in this process. Different factors can affect the aging of the skin for the human such as lifestyle, diseases, and the environment. Using a facial feature alone is not evocative because these features are common in individuals. Therefore, various algorithms and approaches are used in the estimations based on facial, gait, and motion features by applying many technologies to capture the images such as the Kinect sensor.

Microsoft Kinect sensor is a motion-sensing device that contains a combination of cameras, depth sensing, and an array of microphones, so it can track the movements, and gestures and interpret the user's actions and voice commands in real-time which is a good technology choice for be used in age estimation, see figure 1 [1].

The developing technologies are used to detect and estimate human age through considering the human-computer interaction, and how individuals use and learn the machine. Age estimation and detection are significant because various areas require different solutions in terms of age-targeted interaction design [1]. As an example, the use of age estimation in the education field, the technologies use the age of the student to obtain the best appropriate difficulty stages and kind of visual instruction on the computer or a system. One more example of using age information is computer or mobile gaming design, kids and teenagers like the avatars, and characters also the game to be fully colored and bright, while adults prefer a serious and profound look game [2]. Moreover, age can be a significant factor in deciding the affordance of web designs in the marketing field because it is related to a physiological pattern of interaction among the users of the website. In addition, the age information is greatly useful for the websites by assisting a computerized interface [3]. This paper presents the age estimation applications, human age estimation approaches, the database used for age estimation, types of features used in age estimation, a few related works that used Kinect sensors in age estimation, and finally the conclusion.

Fig. 1. Microsoft Kinect sensor V2 [4]

1. Age estimation applications

Various kinds of applications in different fields use age estimation such as:

a. Healthcare: Healthcare specialists' perceptions and attitudes toward aging show a significant role in healthcare distribution, with attitudes towards aging, knowledge, and concerns about aging positively affecting the quality of care provided to older persons. These results highlight the importance of addressing age-related factors in health care to improve services and outcomes for older individuals. Many studies have examined how age affects individual evaluations of health issues, suggesting that older respondents may value health more than age, especially in terms of information relating to transportation issues. Furthermore, the association between access to treatment and health outcomes varies by age and sex, particularly among older adults, and access to care is reported to play a role, especially in health outcomes. Results indicated that the oldest respondents valued health information less than their age, especially for information describing problems in the movement domain [5] [6].
b. Customer services and marketing: Customer services and marketing have a vast affected on age estimation including various factors of client behavior and carrier perception. Research shows that age-associated elements can affect purchasing selection marketing tactics inside special sectors, consisting of banking with prominent variance determined in client behavior among individual and young clients. Older purchasers can also show off distinct behaviors in comparison to more youthful purchasers, with preferences for well-established brands and higher loyalty stages to specific brands [7]. Considering the age-related alternatives, wishes, and buying styles is important for organizations to modify their strategies on advertising and marketing. age estimation can impact customer support and marketing by way of influencing buying behaviors, emblem loyalty, purchaser satisfaction, and the effectiveness of advertising strategies tailor-made to unique age organizations [8].
c. Forensic Science: In forensic science, age estimation can be critical when identifying unknown human remains, as it can help decrease the list of potential missing individuals and assist in investigations. It's also can be used to determine the adult status of suspects when their chronological age is unknown, which is important for legal purposes. It can also help reconstruct the biological profile of an unidentified victim [9]. Age detection is significant in disaster victim identification and immigration cases. In mass disaster situations, age estimation from teeth or other biological evidence can help identify victims by reducing the list of potential missing individuals. Immigration cases can be helpful when an individual's age affects legal protection status [10].
d. Security and surveillance: Analyzing facial features in the real-time video to estimate a person's age and then evaluating the predicted age to recognize a long time of individuals of hobby, safety structures can potentially discover precise people within the footage. The age estimation can be included in man or woman identification across a couple of cameras or in video sequences with varying environments, as well as hyperlink detections of the persons in unique video segments even with the modification of their appearance. It also played an important factor in monitoring age-restricted areas such as gambling establishments, and in estimating crowded demographics for security assessments or event planning [11], [12], [13], [14].

e. Archaeology: Age estimation is a crucial tool in archaeology allowing researchers to date artifacts, perceive individuals, and reconstruct populace demographics. Automated age estimation of archaeological artifacts the use of system learning strategies, can substantially enhance the performance and accuracy of artifact relationship and categorization. By studying the traits of artifacts, these strategies can assign them to specific time intervals, allowing researchers to better understand the chronology of archaeological websites. Age estimation of the human skeletal leftovers is important for guessing out individuals and reconstructing the demographics of beyond populations. By figuring out the age distribution of individuals within a populace, archaeologists can reconstruct the demographics of beyond societies [15], [16].

2. Human age estimation approaches

Several approaches have been used for age estimation purposes, including:

a. Motion blur: this method estimates motion blur parameters entirely based on a modified random transform and categorizes the input facial images into categories based on the expected blur. Then apply an appropriate age estimate in each class. This technique is found to be robust to photo motion blur [17], [18].
b. Deep learning age estimation: The deep learning method is used for age estimation, researchers implementing it used the VoVNetv4 network which is a type of convolutional neural network (CNN) architecture. This method detects human falls based on age statistics, classifying persons as aged (60), teens, or young adults. It combines age with Open-pose body key points to track the age and location of the person [17].
c. Auditory perception: auditory perception is used by the researchers as a biometric trait to verificative, classify and estimate the age of the human. Support Vector Machine (SVM), Neural Network (NN), and Random Forest (RF) are a kind of technique used to expect age from auditory perception [19].
d. Gait-based 3D: various approaches are used 3dimentional gait data to estimate human age. Systems on machine learning use a 3-dimensional skeleton database captured by a Kinect sensor implemented to build real-time age detection [20], [21].
e. Skeletal: evaluating the skeletal remains of humans is an important recognition of forensic anthropological and age detection. The method entails bodily, radiography of the left hand and dental examination. The amount of epiphysial union of the clavicles additionally presents essential facts [20].
f. Kinect-based physical function assessment: An examination to evaluate the feasibility of using a Kinect-based system to measure physical function within the aged for home-primarily based care. The measure has confirmed mild to incredible reliability and a high relationship with physical examination for practical checks like gait, balance, and mobility [20].

These above procedures span image processing such as deep mastering, auditory belief, gait evaluation, and skeletal evaluation. Kinect sensors were leveraged in a few studies because of the low cost and marker-much less movement seize competencies. However, challenges persist in regions like motion blur, sign noise, and 3D gait evaluation that require in additional studies.

3. Human Age Estimation database

This section presents the most databases or datasets used for age estimation purposes:

a. **FG-NET:** this dataset is available publicly and contains face images of different persons at different ages, each subject with twelve age-separated images. The database was collected from 82 persons, ranging from 0-69 years, the total number of images is 1,002. Many researchers used it for face detection and age estimation [22], [23].
b. **UTKFace** database: this database is a large-scale facial image captured from individuals whose age ranges from 0 to 116 years, about 13,707 face images marked with gender, age, and society with differences in pose, expression, resolution, and other factors. It is valuable for research in age estimation, face detection, and analysis [24].
c. **CACD database:** CACD (the Cross-Age celebrity dataset) which is also a large-scale database with 16,400 images collected from the internet for 2,000 personalities. A search engine gathered the images with personalities birth years (2004-2013) and names [25], [26].
d. **CLAP2015 Database**: this database is used for superficial age estimation, where each image is evaluated with at least 10 annotators, and the mean evaluation is used as the ground truth [27].
e. **Yamaha Gender and Age (YGA) Database**: A large database comprising 8,000 facial images of persons their age range from 0 to 93 years, collected outdoors [24].

Furthermore, there are other kinds of databases such as the OUI-Adienc database [28], 2. Ni's web-controlled database[29], 3. Hybrid organic-inorganic perovskites (HOIP) [30], 4. Lotus Hill Institute database (LHI) [31], 5. Caucasian Face database [32], 6. Waseda human-computer Interaction Technology – Database WITE-DB [33], 7. Illumination and Expression (PIE) database [34], 8. Iranian face database [35], 9. Face Recognition Technology Program database (FERET) [36], 10. UIUC-IFP internal aging database [37], 11. MORPH database [38], 12. The Face Recognition Grand Challenge Database (FRGC) [39], 13. Life span database [40], 14. GROUPS database [41], 15. FG-NET database [42], [22].

These databases offer a variety of facial images annotated with age, gender, and various attributes that allow researchers to enhance and evaluate age estimation algorithms. The availability of large-scale annotated data sets has been critical to modern progress in this field.

4. Types of features used in Age estimation

In this section, a standard feature used for age estimation, and the feature captured by the Kinect sensor that can be used for age estimation are presented:

4.1 Standard features

An age estimation standard features can be classified into two categories:

1. Physiological features such as [43], [44]:
   a. Teeth: (tooth length, width, volume), (root length and width), (plub length, width, and area), Crown (height, width, labio-ligula, Bucco ligula measurements), and (tooth corona index, coronal plup cavity height).
   b. Speech or voice patterns
   c. Gait
   d. Signature dynamics
   e. Hand geometry.

2. Biological features [43], [45]:
   a. Body: Height, width, diameter measurements of short and long bones, curvatures, and direction patterns in fingerprints or palmprints.
   b. Craniofacial growth.
   c. Facial wrinkles and texture.
   d. Skin elasticity and color.
   e. Voice pattern alteration.
   f. Public synthesis.
   g. Auricular surface change.

h. Acetabular surface changes.
i. Sternal end of ribs.
j. Closing of cranial sutures.
k. Facial elasticity, wrinkles, texture, and color.
l. Union of the whole body.
m. Manubrium of the sternum appears.
n. Retirement benefits.
o. Pension claims.

The two categories are used in various algorithms including manual, semi-automated, and automated to estimate the human age.

4.2 Features captured by Kinect sensor

The features which can be captured by the Kinect sensor used in age estimations are:

1. Facial features [46], [47]: the depth RGB color facial images captured by the Kinect depth-color sensor permit more inclusive facial analysis used to extract aging-related features like wrinkles, skin, and craniofacial growth patterns, as shown in figure 2.
2. Gait features [46],[48]: gait patterns and dynamics changes with the progress can be captured by the Kinect, features like arm swing, head pitch, hunched posture, and stride are the most prominent aging features in gait. It is shown that gait analysis is effective for classifying different aging groups (young, adults, and elderly), see figure 3.
3. Skeletal and body features [49]: the skeleton and body features captured by Kinect can provide measurements of the body dimensions, bone lengths, joint positions, and angles between joints that evolve with age, these are used as indicators of physical maturity and aging, see figure 4 .

In summary, the Kinect sensor's ability to capture 3D depth information, skeletal tracking, and gait dynamics makes it a promising tool for extracting age-related features from both the face and body, which can be leveraged for automated age estimation. The search results highlight the potential of using Kinect data to develop robust age estimation models.

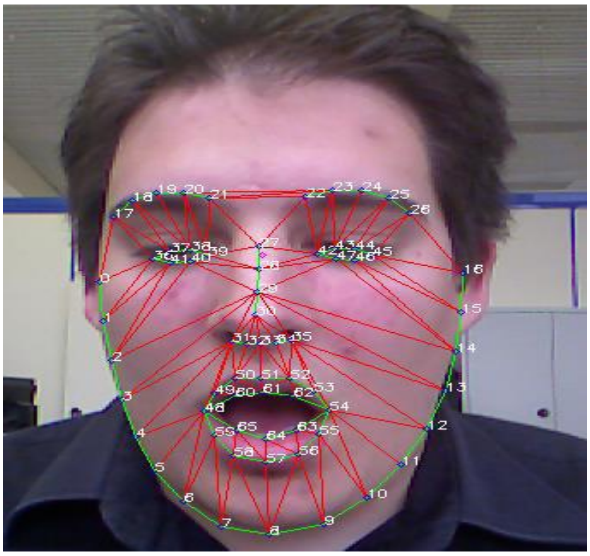

Fig. 2. Facial features captured by Microsoft Kinect sensor [50].

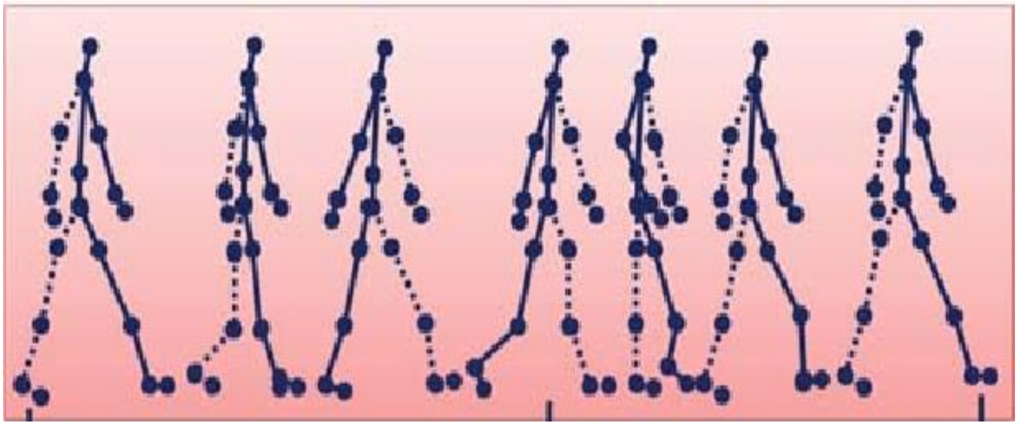

Fig.3. Gait-based features captured by Microsoft Kinect sensor [51]

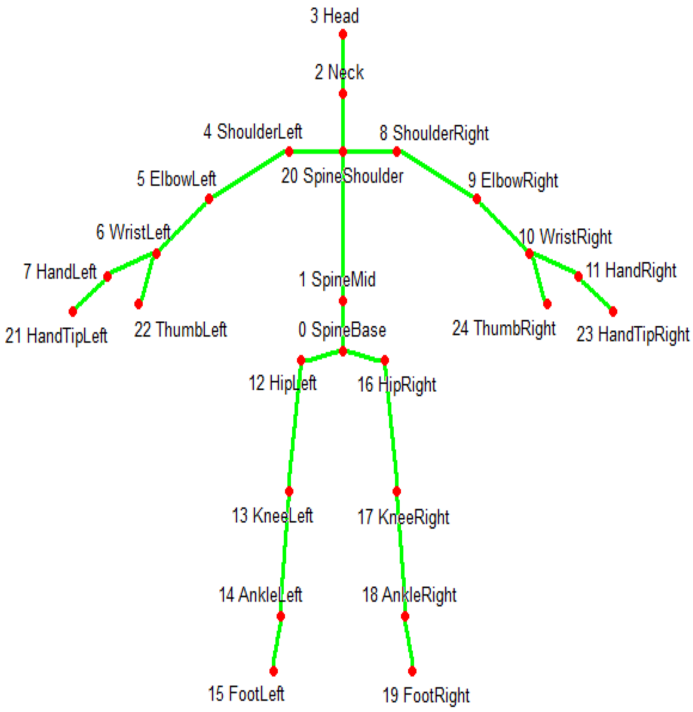

Fig. 4. Skeleton body features captured by Microsoft Kinect sensor [4]

5. Age estimation using Kinect sensor

First, the Microsoft Kinect sensor is a depth-sensing camera, it is in various applications such as individual facial analysis, face recognition, and age estimation. It can capture 3D images of the body and face, skeletal joints position for the whole body, and track 6 persons at the same time, provides its features then the machine learning algorithms are used to analyze the features like texture, shape, geometry of the face and skeleton or gait for the body to estimate gender and age [52]. It is important to know that the accuracy of the estimation may vary based on factors like lighting, expressions, and pose.

5.1 Limitation of Kinect sensor in age estimation

The Kinect sensor has a limitation that affects the accuracy of estimation, including [53], [54], [55]:

1. Partial range and angular coverage.
2. Distortion in skeleton joint estimation leads to inaccuracies in estimation based on the body skeleton.
3. Issues related to accuracy and precision movements, especially in complex and fast-paced activities.
4. The dependency on environmental factors such as lighting conditions, space constraints, and sensors placed for optimal functioning.

5. The availability and quality of training Kinect data can impact the accuracy and generalizability of age estimation.

5.2 Improvement's algorithms and approaches

Based on the above limitation, a question arises "Are there any specific algorithms that improve age estimation using Kinect sensor?", the answer is "YES", some of the improvement algorithms are [46], [48], [56], [57]:

1. Randomize decision Forest Algorithm can be used to improve the resolution of the Kinect depth images, which can enhance the accuracy of age estimation.
2. RGB-D Image Fusion: this can provide more information about facial aging.
3. 3D Descriptors: Applying classical 2D feature extraction processes to depth maps can help in describing the local distribution of aging effects and depth progression from the depth map, and enhancing age estimation
4. Gait Analysis: Analyzing gait patterns using Kinect data can provide additional features for age estimation, such as stride length, head pitch, and arm swing, which are more robust to occlusions and changes in depth.
5. Machine Learning techniques: Techniques like Support Vector Machine and Convolutional Neural Networks (CNN) can be used to learn optimum model parameters from the training facial images of different range ages to improve age estimation accuracy

5.3 Most related works use Kinect for age estimation

As mentioned previously, the Kinect sensor is used for various purposes such as facial and body analysis tasks but there is a limited study, especially on the use of the Kinect sensor alone for age estimation purposes. The following studies and articles are the most related works that discuss age estimation or detection using Kinect sensor technology:

- Azhar, Muhammad et al. (2023), presented a real-time age detection system utilizing machine learning on 3D gait skeleton data captured by the Kinect sensor. First, they built their large f database and captured it using a Kinect sensor consisting of 3-dimensional skeleton joint positions from 273 volunteer persons aged from 7 to 70 years. Their system consists of training and testing phases where gait patterns are captured and analyzed to detect the age in real time. Machine learning methods are used to classify the gait patterns into various age groups. The accuracy of the age estimation they obtained is 98.0% using the Classical Liner Regression Model (CLRM) with nine features (right shoulder, elbow, and hand, left knee, ankle, and foot, right knee, ankle, and foot)[58].
- Mousavi et al. (2018) presented a way to estimate human age from RGB-D images, they detect and extract faces from the depth images and then utilize the information in their approach to train a deep learning algorithm on a database they labeled RGB-D images to estimate the age for the persons and compared the results obtained with using RGB alone. The accuracy they obtained is low [59].
- Nabila Mansouri et. al (2020) discussed the use of Kinect in face analysis and age estimation, they mentioned that most of the exciting studies using Kinect focused on gender recognition, face recognition, and overlooking age estimation, showing that it can improve age estimation accuracy because of its ability to captured RGB-D images. Moreover, the authors highlight the importance of the use of Kinect in proceeding age estimation approaches and underscore the significance of leveraging for more precise and effective age estimation [46].
- Gabriel Fuertes Muñoz et al. (2021) The authors presented an interactive healthy assisted aging based on the Kinect sensor with a graphical user interface. Their Experiments involved 57 participants aged between 65 and 80, they performed the same physical exercise 6 times in fifteen days. The results of the work provided an important indication of the support and usefulness of the system in helping older persons of various ages. The accuracy in measuring improvement in

physical accomplishment of the elderly. The experimental results showed that no matter their poor technological abilities, older people can adapt simply to the usage of an interactive assistance tool for active aging if they revel in clean advantages [60].

6. Conclusions:

The conclusion of this paper can be summarized in:

- Kinect sensors can provide useful RGB-D depth images which can be used in various applications, these applications give an assist to the individuals in their lives.
- Kinect sensor has been used for various facial analysis tasks but, there is limited research specifically on age estimation using Kinect depth data alone because of the limitations in resolution and the effect of occlusions in the Kinect data need to be addressed.
- Studies indicate that fusing images with RGB information is important to get reliable age estimates and more research is needed on how to best leverage Kinect's depth data for age estimation.
- Algorithms and techniques can be used to enhance the performance of Kinect-based systems for age estimation and detection such as Random Decision Forest.
- studies suggested that using three-dimensional descriptors on Kinect maps could be a promising approach for automatic age estimation.
- Also, using a large publicly available database and the improvement algorithms with machine learning techniques can enhance the accuracy of age estimation and detection.

Acknowledgment

The authors are thankful to Mustansiriyah University hosted by the Department of Computer Science in the College of Education. Baghdad, Iraq, for supporting the investigations.

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