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Auditory perception based system for age classification and estimation using dynamic frequency sound

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Abstract
Human age is a crucial factor in social interaction. It determines the way we interact with others. It is also a relevant forensic issue that can provide helpful information in legal and criminal investigations. Thus, human age estimation has a wide range of real-world applications related to human computer interaction and forensic sciences. Based on auditory perception, in this paper, we investigate a new biometric trait for human age classification and estimation. For this purpose, several techniques of Machine Learning, including Random Forests (RF), Support Vector Machines (SVM), Linear Regression (LR), Polynomial Regression (PR), Ridge Regression (RR) and Artificial Neural Networks (ANNs), are used to estimate the age of the volunteers. To evaluate the performances of our experiment, a dataset of 837 tests have been collected with different ages ranging from 6 to 60 years. The results show a good accuracy between 86% and 92% of reasonable classification and 98.2% of good age estimation with a root-mean-square error of 2.6 years. Results are found to be significant and show that auditory perception is one of the practical interests in real-world applications. The dataset we used will be made publicly available online.

Keywords Auditory perception · Age estimation · Age group classification · Biometrics · Forensics

1 Introduction

In this modern world, where technology has almost taken over every aspect of life, biometrics offers a notable environment to make our lives more comfortable and secure. Biometrics are distinctive physical or behavioral measurable characteristics that are used for identification or verification. While identifying an individual with actual age or linking him/her to a specific class of age is an important issue to address in the biometric society. Humans normally try to recognize each other through different characteristics such as voice, face, gait, location , clothing etc. Combining all these attributes provides the identity of an individual.

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In the old era, it was easy for people to recognize each-other because communities were relatively small. With the exponential increase in the global population, the human community feels the need to have a sophisticated biometric system for identification that can precisely provide maintenance, recording and, securing the personal information of individuals.

Among biometric approaches, human age is an important individual trait and useful signature. It received substantial attention from scientific communities of biometrics, computer vision, and pattern recognition. The interest is driven by the need for smart and secure systems in human-computer interaction and forensic science analysis. Therefore, human age study encompasses security and forensic tools by bringing into consideration human's physical or physiological appearances or behavioral features. Most of the studies are focused on age estimation, mainly, either from the face or voice analysis [29].

2 Related work

In this section, we review state-of-the-art for human age estimation using physiological and behavioral biometrics.

2.1 Physiological biometrics for age estimation

The type of physical characteristics used for biometric age estimation includes face, fingerprint, DNA, dental information etc.

Face is the most used physical biometric feature for age estimation. Indeed, face conveying a significant amount of information such as identity, ethnic group, gender, emotional state, and age. Yet, despite the fact that the age of a person is an important attribute that determines the way we interact with him or her, there has been little research focused on developing systems for automatic age estimation as compared to human identification from face photos [5, 12]. From the technical point of view, different classifiers based on quadratic functions, shortest distance, and neural network are performed [24] while for age classification, a dropout-SVM that avoids over-fitting is used [12]. While the error of estimation from face image was around five years [12, 29], it appears that human still achieves better results than machines on age estimation with an age estimation errors of 3.64 years [12]. Wei shen et al. [48] proposed a Deep Random Forests (DRFs) approach with a strong mathematical model by using CNN and achieved the MAE value of 2.96 years for human age estimation using facial features. Tingting et al. [52] used Three Stage-Network (TSN) based on facial features using deep neural networks. For MORPH dataset it shows an accuracy with MAE value of 2.85 years. Dornaika et al. [11], used two different regression functions such as norm error and adaptive loss function. They tested the model with public datasets and achieved 2.74 root mean error value for age estimation.

Fingerprint age estimation studies were found to be invasive. Changing a print throughout the inspection or example during physical development or print dissolution. Thus, it is not allowing systematic analysis of single print degradation procedures using time series analysis. Neither of them could include specific outcomes regarding performance assessment of age and error values. A database consisting of 500 fingerprints collected from the ten fingers of fifty individuals forge estimation. The images taken from the fingers were converted to binary images with a specific matrix value. Using K-Nearest Neighbor (KNN) classification algorithm, 93.3% and 83.0% of accuracy were achieved for males and females [8].

Rudolf Haraksim et al. [18] used a database of 60,000 fingerprint from different age range (5-25 years) to estimate the age of human based on the growth of the fingers. They demonstrated the possibility of age estimation using fingerprint with a higher precision and it was limited for specific age range.

DNA is one of the physical features used for human age estimation and identification. Indeed, the forensic individual age estimation with DNA approaches have gradually risen in the past five years. Morphological inspection or radiography was initially used for forensic age estimation, and later molecular approaches have been explored. Forensic age estimation predictor used blood samples to estimate the age of humans, but recently scientists are also exploring tissues to utilize it for age estimation. Recent advancements in the field of age estimation using DNA methylation, the predictive accuracy has increased the potential of the system and its accuracy with an error value of ±4 years [13]. The human age estimation from dental observations has been studied, and several techniques have been proposed accordingly. For children, they are based on dental maturation and may be divided into those using the atlas approach and those using scoring systems. For adults, morphological and radiological techniques are used [56].

Dental age estimation in scientific literature, presents several data sources on various approaches, the technical execution, and the mechanisms following them. Growth features such as mineralization, gingival clinging, cementation of quantities, or decrease of pulp space can be used to evaluate dental age. In a German populace, Paewinsky et al. affirmed the appropriateness of Kvaal's procedure to digitized all-encompassing radiographs and noted improved exactness and more prominent coefficients of connection. The outcomes uncovered the most grounded connections between the readings and age. The results show upper horizontal incisors and a straight coefficient of relationship r=-0.916 with a standard deviation of 6.4 years [35]. Meinl et al. evaluated the utilization of the improvement of the relapse recipe by Kvaal and Paewinsky to OPGs from an Austrian populace and found that immediate execution of the relapse formulae brought about a genuine age underestimation going from 31.4 to 47.1 years [32]. Maryum et al. [15] presented the idea of age estimation by using the pulp-to-tooth ratio for dental images through artificial neural networks. All the teeth can be used for human age estimation, while they have chosen canines because they have fewer chances to be rotten, having large roots and pulp, and idealized in older individuals. The performance of the proposed system was acceptable with a mean absolute error value of 4.12 years.

2.2 Behavioral biometrics for age estimation

Behavioral characteristics are related to the pattern of human activities such as voiceprint, gait, keystroke dynamics and signature.

Voice is one of the behavioral characteristics that are used for identification and authentication. It is commonly referred to a voiceprint. Basically, voice recognition systems measure and extract features from a user's speech signal. Voiceprints have been used in several forensic approaches to identify the gender, age, and language of a user automatically. Among these approaches, the automatic age is estimated and classified into an age group using parallel phone recognizer, Dynamic Bayesian Networks, linear prediction analysis, gaussian mixture models with MFCCs [26], HMM-based classifiers [47], Gaussian Mixture Model (GMM) supervectors and Support Vector Regression [9]. Automatic speaker age estimation is proved possible with an absolute mean error, which varies from 4.7 to 10 years [29] and classification accuracy of around 50% [47].

Gait signatures are also one of the best behavioral biometric modalities to estimate the human age [27]. With the help of gait features, it is possible to differentiate between males, females, even in the same age group. However, there are very few studies on gait-based age estimation and age group classification in comparison to face-based studies. Semwal et al. [46], used Deep Neural Network (DNN) as a classifier and achieved 92.3% of the accuracy by selecting 17 gait features while using Extreme Machine Learning (EML) based on cellular automata, 60% of accuracy is achieved [44]. For gait-based age estimation, the deep learning-based convolutional network has been used for a person's age estimation, and classification [41] and a baseline algorithm using Gaussian process regression with silhouette-based gait features is provided [31, 33]. The mean absolute error of 8.2 years is achieved [31]. Haiping et al. [57] proposed Global and Local Convolutional Neural Network (GL-CNN), that reduces the MAE value to 5.12. The GL-CNN has three local sub-networks, and has the ability of learning the global structure and local information from the head, body, and feet.

Keystroke dynamics are studied as well from the perspective of age detection. With the help of this technique, the exact age cannot be estimated, but it can be utilized just to differentiate between kids and adults. A multi-layer perceptron shows that the age can be detected with a probability that it is far from the uniform distribution with a rate of success of 72% for two classes and 64% for four classes [53]. In previous work, distinguishing child Internet users from adults shows that the accuracy rates above 90% were achievable with support vector machine or linear discriminant analysis classifier [54]. The typing patterns differ from the user's normal position, which generates a recognition error of genuine user for influencing the accuracy [38].

2.3 Motivations

The perception is the human ability to interpret information that our different senses receive from the environment. The audition is the sense that allows us to perceive and localize sounds. The ability to receive and interpret these sounds that reach the ears or human auditory system through audible frequency waves transmitted through the air or other means is thus called auditory perception.

While we are 16 years old, our highest audible frequency is around 18000Hz. At 30 years old, it decreases to around 15000Hz. This means that with the increase in age, the highest audible frequency decreases as well. Consequently, there is a correlation between age and audible frequency [19, 39, 51, 58]. Therefore, hearing loss occurs over time due to the damage of hair cells in our auditory system [2, 16, 34, 50].

Considering the hearing loss as a factor, age can be estimated through the auditory system. Some researchers successfully demonstrated the maximum audible threshold for human according to the age, such as by dragging the attention of the people through a mosquito frequency sound. Despite that in literature, it is mentioned that human has the capability to hear a sound of 12Hz under favorable conditions [2], and the commonly stated range of human hearing is from 20Hz to 20,000kHz [39, 51, 58].

Contrariwise, research in the field of human age estimation through auditory perception has been introduced in our previous work [19] for the first time. In this paper, we introduce a more accurate and enhanced system with better performance. In order to study in a better way, the correlation between age and auditory perception, the aims to achieve three objectives in this research:

- *Demonstrating the feasibility:* the separability between different age groups based on the auditory perception is studied.
- *Classifying human age onto an age group using the auditory perception:* different age groups are used, and the performances of the classification are compared.
- *Estimating human age from the auditory perception:* different regression models are compared to find the best one for forensic age identification from the auditory perception.

2.4 Paper organization

The rest of the paper is organized as follows. In Section 3, we present the proposed auditory perception-based method, materials, and protocols to demonstrate the separability between the different age groups, the age groups classification, and the age estimation. In the Section 4, evaluations, and performances of different proposed approaches are discussed. Finally, in the last Section 5, a conclusion to this work, a set of perspectives and paths for our future work, is delivered.

3 Materials and methods

The flow chart of our proposed auditory perception-based age study approaches is shown in Fig. 1. First, the auditory system is stimulated using a dynamic frequency sound (see Section 3.1). After, the responses of the auditory system are registered in a dataset to analyze the separability between the different age groups (Section 3.2), to classify the perceived responses into an age group (Section 3.3) and to estimate the age of a volunteer (Section 3.4). More details about the different parts of our approaches are given in the following sections.

3.1 Protocol of stimulation

The human auditory system is stimulated by generating a dynamic sound waves, according to the following model:

$$x(t) = A_0.sin(2\pi.\phi(t).t), \tag{1}$$

Where $\phi(t) = \alpha.t + \phi_0$, A_0 stands for sound amplitude, t stands for time, ϕ_0 is the initialization frequency, and α stands for the increasing/decreasing frequency speed.

Therefore, each volunteer is supposed to participate in six experiments, as represented in Fig. 2 using algorithm 1.

For each protocol, the system requires interactivity, as shown in Fig. 2. The dynamic sound is generated with an increasing frequency. In this experiment, four different protocols

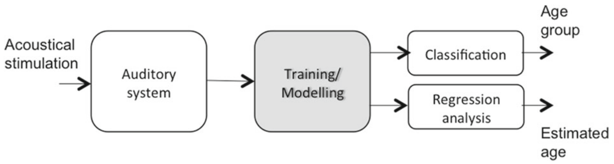

Fig. 1 Flow chart of the proposed auditory perception based age classification and estimation approaches

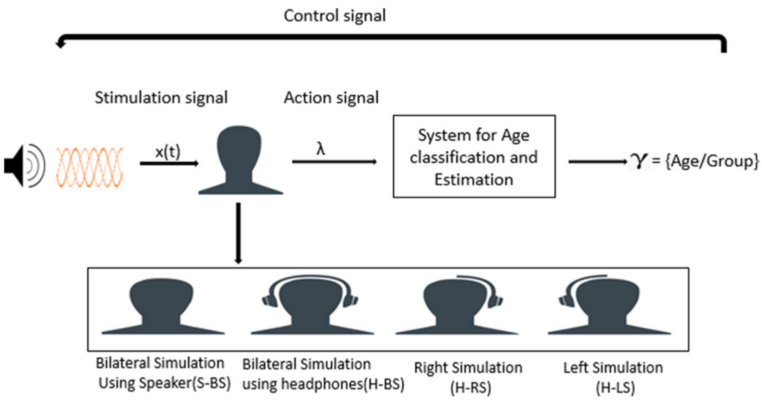

Fig. 2 Flow diagram of our proposed approach

with speaker (S) and headphone (H) are considered, namely: Bilateral Stimulation (S-BS), Bilateral Stimulation (H-BS), Right Stimulation (H-RS), and Left Stimulation (H-LS). In the first protocol, the stimulation duration is set to t_1, t_2 and t_3. This protocol allows defining the most suitable stimulation duration. In the remaining three protocols, headphones are used by considering:

– Bilateral Stimulation (H-BS),
– Right Stimulation (H-RS),
– Left Stimulation (H-LS).

Each volunteer should achieve a manual action to stop the system if no sound is heard. Basically, the stimulation is conducted according to two modes:

– first mode: the sound is generated and increased from the lower frequency (20Hz) to the higher frequency (20,000Hz). The volunteer stops the stimulation (e.g. keyboard action), once no sound is perceived,
– second mode: a second stimulation is triggered automatically once the volunteer completes the first mode action. In this case, the generated sound frequency decreases from the higher frequency (20,000Hz) to the lower frequency (20Hz). The volunteer stops the stimulation once the sound is perceived.

Algorithm 1 Auditory perception based human age estimation.

```
Result: Estimated age
initialization;
while freq do
    test1 = freq(min-max);
    user-feedback=[TAB];
    test2 = freq(max-min);
    user-feedback=[TAB];
    aver = round((test1+ test2) / 2);
end
Regression-model;
Output= Estimated Age
```

3.2 Separability between the different age groups according the auditory perception

Human auditory perception is a strong biometric feature to discriminate against the age of a person. To prove that, Linear Discriminant Analysis (LDA) is used [14]. With this methodology, the ratio of within-class variance to the between-class variance is maximized with the objective of reducing the variation of data in the same class and increasing separation between classes. Therefore, solid boundaries between the classes are built, making it a linear classifier. The linear combination of features that characterizes or separates classes is found using LDA, which gives a better understanding of the distribution of the data features [37].

LDA can handle the case where the number of volunteers in each class is unequal. It is performed on subsets of conditions using three features that correspond to two frequencies. The three-dimensional features matrix is projected onto a lower-dimensional space by maximizing the inter-class variance while minimizing the intra-class variance. The axes of the projected data called linear discriminant and presents the maximum separation between the different age groups, hence it will offer a visual confirmation, or not that age groups tend to be well separated or not considering the registered audible frequencies.

3.3 Classification of the auditory perception into age groups

The second part of this work is concerned with the classification of different auditory perceived responses into age groups. Two supervised learning methods are used: Support Vector Machine (SVM) and Random Forest (RF), . These two classifiers are among the most widely used in computer vision and pattern recognition applications although their performance guarantees have been proven.

Support Vector Machine (SVM): were originally proposed by Boser, Guyon and Vapnik in 1992 [3, 6]. SVMs constructs a set of hyperplanes that maximize the separation, or margin, between samples of the different classes. The sets to discriminate could be not linearly separable in their original space. Thus, it was proposed that the original finite-dimensional space be mapped into a much higher-dimensional space, presumably making the separation easier in that space. Several transformations or kernel functions are evaluated. Multiple values for gamma and cost has been tested ($gammsea = o.5, 0.8, 1, 2$ and $cost = 10^-1, 10^1$). The best results were achieved with radial kernel, $gamma = 2$ and $cost = 10$.

Random Forest (RF): were proposed by Leo Breiman in 2001 [4]. RF is a set of larger decision trees that are created on a bootstrap sample of the training data by using a random selection of variable subsets. Every tree of the forest then votes to determine the sample's class, and a majority vote makes the final decision. The RF classifier is built with recommended values by Breiman for the number of decision trees, which is equal to 500 and the number of features used to split the node in the decision tree growing process denoted by Mtry. It is fixed to 0.10, which is quite close also to the recommended value by Breiman ($Mtry = \sqrt{p}$ where p is the feature vector size, p in our experiment is 3).

Ridge Regression (RR): is normally used for regression problems. We have used it for classification problems by modifying the response label and fits the model to normal. It also helps to mitigate the problem of overfitting by minimizing the training error. Thus, RR controls the coefficients by keeping the borderline linear.

Artificial Neural Networks (ANNs): illustrates the initial neural network model using the least-squares method to calculate the weights that are then used for calculating the activation function. The proposed approach is that the transformed samples have a common structure of sparsity in each class, unlike other methods. The least-square regression model imposes an inter-class sparsity restriction that significantly reduces the sample margins of the same class, whereas samples from different classes will show an increase. Such variables support the way regression is transformed more compactly and discriminated, thus producing better results than others.

Approach of classification: stratified k-fold cross-validation is performed using SVM and RF classifiers with k=10. Cross-validation is a technique to evaluate predictive models by partitioning the original sample into a training set to train the model, and a test set to evaluate it [1, 10, 17]. To optimize the parameters of the algorithms, loops of cross-validation are used by further splitting each of the 10 original training datasets into smaller training datasets and validation datasets. For every combination of the parameters of the classifiers, cross-validation performance is computed, and then the best performing parameters inside the loop are chosen. Then, classification with the best parameters is applied to the original testing dataset [42, 49]. The ultimate performance has been obtained by this procedure that was built using the training dataset. Our 10-fold cross-validation based approach for testing and evaluation is summarized in Fig. 3.

3.4 Age estimation based on the auditory perception

Each age group is well discriminated after quantifying the datasets statistically. In this section, a regression model has been designed in order to estimate the age of a volunteer.

In this work, several techniques have been used: Regression Forests (RF), Support Vector Regression (SVR), Linear Regression (LR), Polynomial Regression (PR), Ridge Regression (RR) and Artificial Neural Networks (ANNs). Regression Forests (RF) are an ensemble of

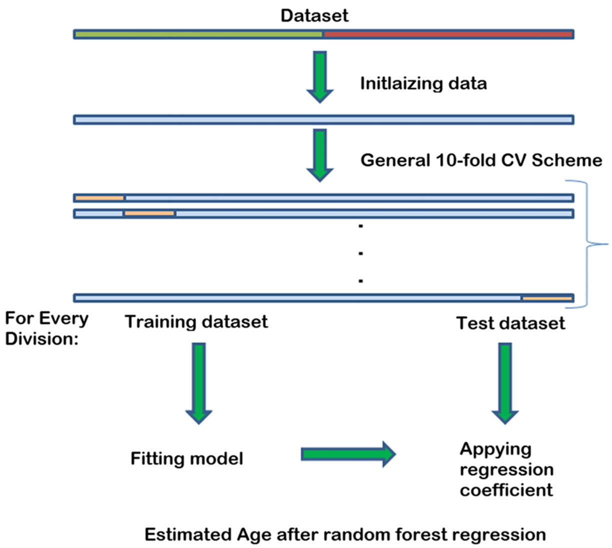

Fig. 3 10 fold cross-validation using random forest

different regression trees. They predict real-valued numbers at leaf nodes using multiple non-linear regression. Support Vector Regression (SVR) uses the same principle as SVM for classification by optimizing the generalization bounds given for regression. A margin of tolerance (epsilon) is considered in the prediction of real numbers, and a loss function is defined that ignores errors that are stimulated within a certain distance to the true value. First, we built a simple model using LR, then tried a different regression model with several combinations variable in order to get the best fitting model [43]. Although PR is a special form of multiple linear regression model [23]. It uses basis functions to build a functional correlation among different variables. RR tries to shrink the parameters, reduces the complexity of the coefficients, and used the technique of L2 regularization [7]. While for ANNs, we used the discriminative least square regression technique. The main concern is to focus on fitting the input features related to output classes [55].

4 Experiments and results

To asses our system, we used DELL corei7 M4700 computer. The minimum distance for a volunteer to take the test from the computer is 12inches. The sound intensity A_0 generated by our system is set to 95db and, the duration $t_1 = 20s$, $t_2 = 40s$ and $t_3 = 60s$.

In the sections below, it will be explained how the datasets are collected, including the analysis process of age groups discrimination. Afterward, the discrimination between the different age groups based on the auditory perception is highlighted. Finally, the results of age estimation are provided.

4.1 Dataset collection

In this experiment, around 140 volunteers from different ages and gender participated in each protocol, and 837 tests are performed, which represent the total number of samples in our database. To conduct one test, a volunteer needs around 10 minutes to complete it. Performing the six experiments is time-consuming, and consequently, many volunteers were not able to complete all of them. For this reason, the number of volunteers for each protocol is not the same (Tables 1 and 2).

The six collected datasets are sub-divided into three age groups and five age groups. As shown in Table 1, a volunteer belongs to:

– Child: if the volunteer conducting the experiment is less than 12 years old,

Table 1 Number of volunteers in each group of the three age groups within the six datasets

Datasets	Child < 12	Teenager $12-18$	Adult > 18	Total
With Speaker				
S-BS (20s)	22	26	93	141
S-BS (40s)	22	26	90	138
S-BS (60s)	22	26	89	137
With Headphone				
H-BS	22	26	95	143
H-RS	22	26	91	141
H-LS	22	26	87	137

Table 2 Number of volunteers in each group of the five age groups within the six datasets

Datasets	Child < 12	Teenager 12 – 18	Young adult 19 – 29	Adul 30 – 50	Aged > 50	Total
With Speaker						
S-BS (20s)	22	26	29	43	21	141
S-BS (40)	22	26	28	41	21	138
S-BS (60s)	22	26	28	40	21	137
With Headphone						
H-BS	22	26	32	42	21	143
H-RS	22	26	27	43	21	141
H-LR	22	26	25	41	21	137

– Teenager: if the age of the volunteer conducting the experiment is between 12 to 18 years,
– Adult: if the volunteer conducting the experiment is more than 18 years old.

Child and teenager age groups are almost balanced, while more volunteers are participating in the adult age group. As shown in Table 2, the two age groups of child and teenager are kept the same as in the dataset of three age groups. The adult age group is subdivided into three groups:

– Young adult: if the age of the volunteer conducting the experiment is between 19 and 29 years,
– Adult: if the age of the volunteer conducting the experiment is between 30 and 50 years,
– Aged: if the volunteer conducting the experiment has more than 50 years.

Around 25 volunteers on each of the six tests participated in the experiment except the adult age group (30-50 y) in which we have more than 40 samples. In order to balance the different age groups, weighting down groups is applied during the next steps of data analysis and processing.

4.2 Separability between the different age groups according the auditory perception

Considering the first protocol, S-BS for $t_1 = 20s$, such that it has been studied after being divided into three age groups and then into five age groups. The LDA was performed, and the samples are projected on the two first linear discriminant axes (LD1 and LD2). The projected data are presented in Fig. 4-a and shows a good separation between the three age groups of child, teenager, and adult. However, the boundary of the teenager class is not well drawn. The data is projected in three-dimensional space, as shown in Fig. 4-b. The three age groups are well separated, and consequently, it is concluded that there is good discrimination between the three age groups based on the auditory perception. For better separability and discrimination, LDA was performed upon the dataset of S-BS for $t_1 = 20s$ divided into five groups. The child and teenager age groups are well separated, but the three age groups of young adult, adult, and aged are more mixed-up, as shown in the projection of data on the two linear discriminants (Fig. 4-c) and on the three linear discriminants (Fig. 4-d).

While considering the second dataset of first protocol S-BS for $t_2 = 40s$, LDA was performed upon the dataset divided into three and five classes. The projection of the samples

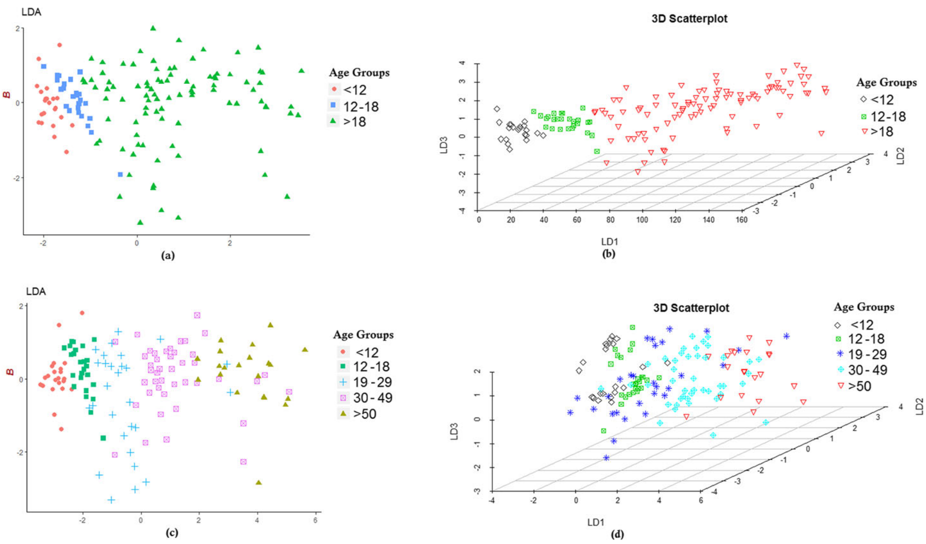

Fig. 4 LDA applied to S-BS for $t_1 = 20s$ dataset divided into three (top) and five age groups (bottom): data projected on axes LD1 and LD2 (a,c) and on axes LD1, LD2 and LD3 (b,d)

into the linear discriminants is shown in Fig. 5 and presents a good separation between the different age groups, but it is not very well isolated as compared to the dataset of S-BS for $t_2 = 40s$. The protocol of S-BS for $t_2 = 40s$ is not much efficient because the data of child and teenager age groups are not well separated.

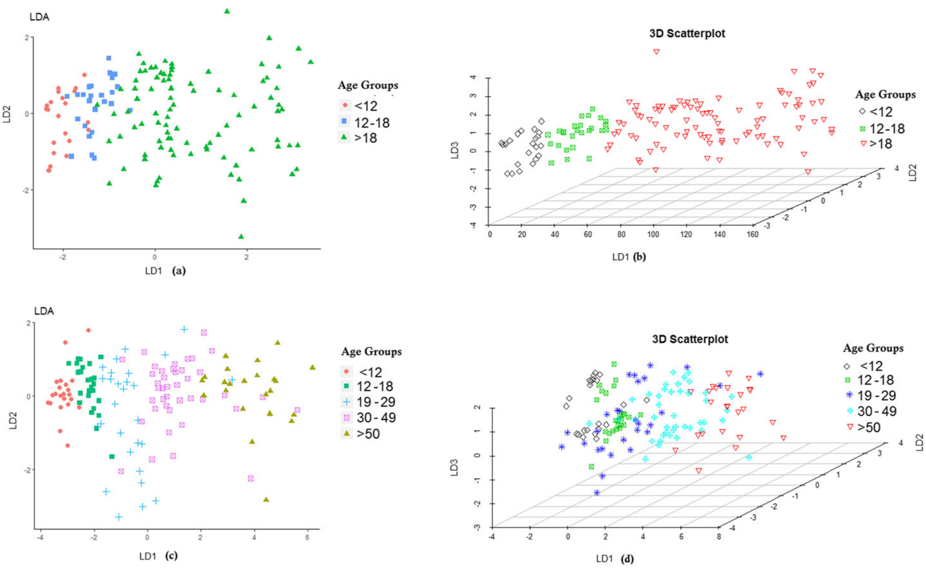

Fig. 5 LDA applied to S-BS for $t_1 = 40s$ dataset divided into three (top) and five age groups (bottom): data projected on axes LD1 and LD2 (a,c) and on axes LD1, LD2 and LD3 (b,d)

The third dataset of the first protocol of S-BS for $t_3 = 60s$ is considered for statistical evaluation. LDA is performed, and the results are shown in Fig. 6. A big similarity between the results is experienced in the projection of the dataset S-BS for $t_1 = 40s$ and the dataset S-BS for $t_1 = 60s$. Indeed, age group samples are highly mixed-up. There is a confusion of data among the different age groups, and it is not well separated as compared to S-BS for $t_2 = 40s$ dataset.

Consequently, in the first protocol S-BS for $t_1 = 20s$ acts better than the protocol of S-BS for $t_1 = 40s$ and S-BS for $t_1 = 60s$. It shows better discrimination of the different age groups. Considering the same procedure as done for the dataset of S-BS for $t_1 = 20s$, the analysis of the protocols such that H-BS for $t_1 = 20s$, H-RS for $t_1 = 20s$ and H-LS for $t_1 = 20s$ are studied to compare and perceive the best protocol that gives the best discrimination among the different age groups.

LDA is performed upon the dataset of H-BS for $t_1 = 20s$ (Fig. 7). It shows through the projection into the linear discriminant less separability between the different age groups than the dataset of first protocol S-BS for $t_1 = 20s$ (Fig. 4). The teenager age group is confused with the child and adult age groups, while the five age groups are not well segregated.

In Figs. 8 and 9, the results of the LDA for the third protocol dataset of H-RS for $t_1 = 20s$ and the forth protocol H-LS for $t_1 = 20s$ after quantifying it for three and five age groups are presented. The results show that the data is not separated properly as compared to the first protocol S-BS for $t_1 = 20s$ dataset.

In conclusion, the protocol of S-BS for $t_1 = 20s$ according to the LDA presents more separability of the age groups than the other protocols. The resulting auditory perceived responses from this protocol can be used for age group discrimination. In the following sections, this separability is quantified statistically: first, by identifying to which set of age

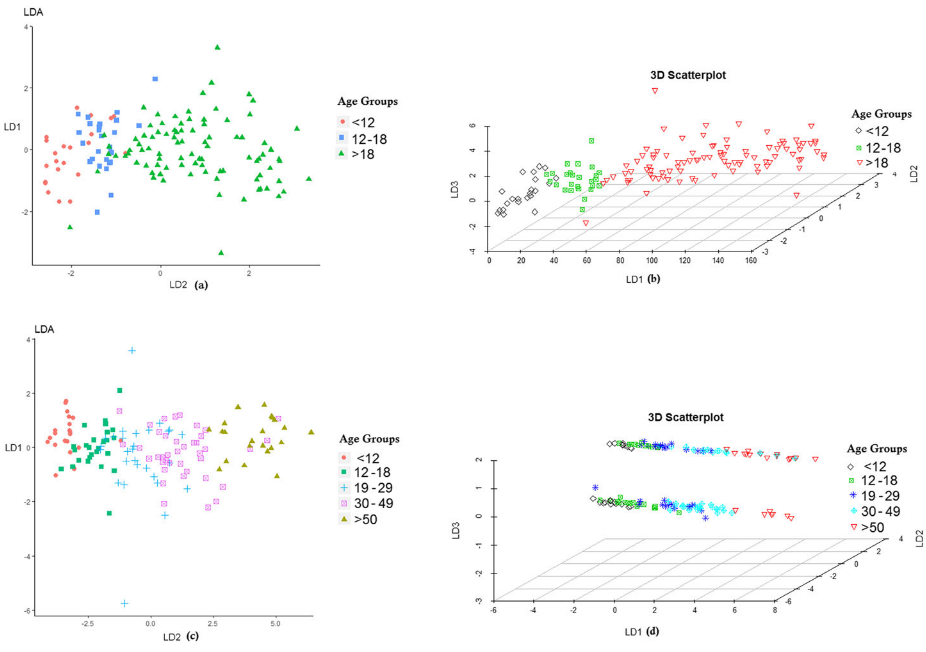

Fig. 6 LDA applied to S-BS for $t_1 = 60s$ dataset divided into three (top) and five age groups (bottom): data projected on axes LD1 and LD2 (a,c) and on axes LD1, LD2 and LD3 (b,d)

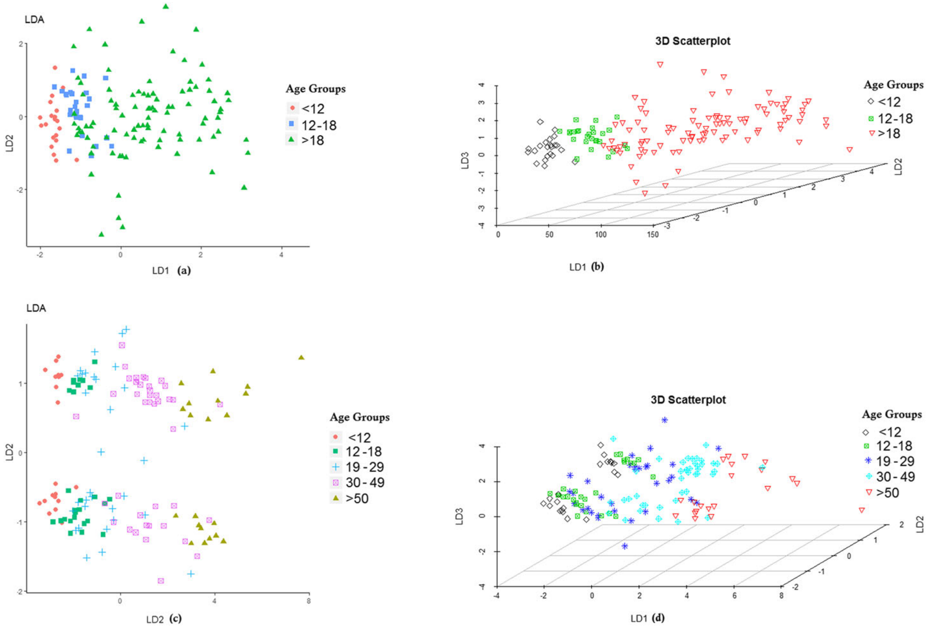

Fig. 7 LDA applied to H-BS for $t_1 = 20s$ dataset divided into three (top) and five age groups (bottom): data projected on axes LD1 and LD2 (a,c) and on axes LD1, LD2 and LD3 (b,d)

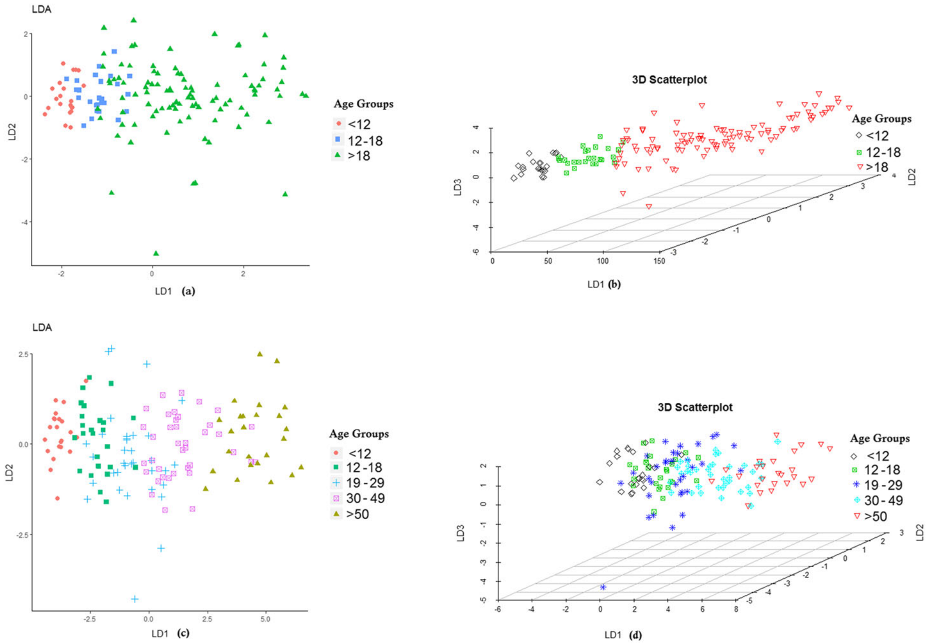

Fig. 8 LDA applied to H-RS for $t_1 = 20s$ dataset divided into three (top) and five age groups (bottom): data projected on axes LD1 and LD2 (a,c) and on axes LD1, LD2 and LD3 (b,d)

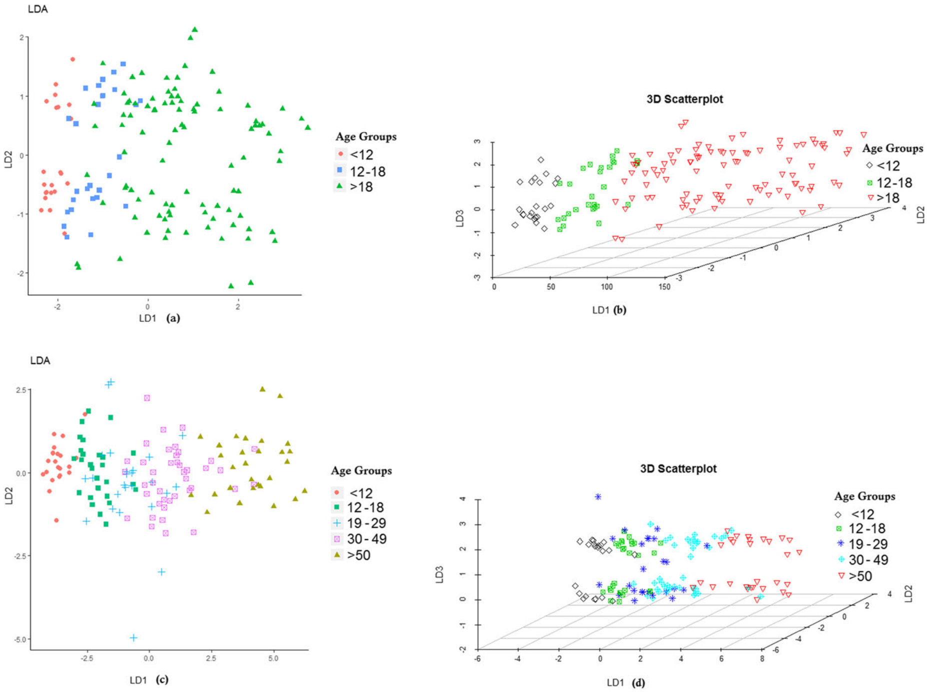

Fig. 9 LDA applied to H-LS for $t_1 = 20s$ dataset divided into three (top) and five age groups (bottom): data projected on axes LD1 and LD2 (a,c) and on axes LD1, LD2 and LD3 (b,d)

groups, a new observation belongs and then studying the distribution of data using statistical hypothesis testing.

4.3 Classification of the auditory perception into age groups

In this section, the classification of the auditory perception into three and five age groups is performed using different machine learning classifiers such as RF, SVM, RR, ANNs. 10-fold cross-validation is repeated 100 times all the classifiers. The final classification rate is calculated and shown in Table 3. The best accuracy of 92% is achieved for the three age groups and the S-BS for $t_1 = 20s$ dataset using RF classifier. For five age groups, the

Table 3 Performances of the classification into three and five age groups

Dataset	RF	SVM	RR	ANNs	RF	SVM	RR	ANNs
	Three age groups				Five age groups			
S-BS (20s)	92%	80%	83%	89%	86%	65%	79%	80%
S-BS (40s)	91%	67%	82%	85%	84%	56%	81%	75%
S-BS (60s)	86%	65%	71%	71%	80%	45%	81%	69%
H-BS	86%	69%	79%	82%	81%	47%	73%	78%
H-RS	86%	66%	74%	72%	80%	50%	66%	69%
H-LS	84%	56%	69%	72%	81%	41%	59%	66%

Table 4 Confusion matrix of the classification using RF classifier of S-BS for $t_1 = 20s$ dataset into three age groups

	Child	Teenager	Adult	Omission	Commission
Child	21	1	0	5%	0%
Teenager	0	25	3	11%	4%
Adult	0	0	93	0%	3%
Correctly classified	21	25	93		
Total	21	26	96		
Overall accuracy	92%				

maximum accuracy of the classification of 86% is also achieved with the S-BS for $t_1 = 20s$ dataset and the RF classifier (Table 3).

To investigate the accuracy of classification for each age group, the confusion matrices of the classification of the S-BS for $t_1 = 20s$ dataset using RF classifier into three age groups (Table 4) and into five age groups (Table 5) are studied. It is shown in Table 4 that the teenager age group has the highest number of responses that are misclassified as an adult age group. And from Table 5, it is evident that the misclassified responses are most of the time predicted as one of the closest age groups. A possible interpretation is that the *a-priori* age range inside each age group is not well defined and could be different for the case of our application.

In our experiment, RF shows higher efficiency in classification as compared to other classifiers. To conclude, there is an important and obvious separability between the different age groups. Thus, the auditory perception is well discriminated in the first protocol of S-BS for $t_1 = 20s$, which corresponds to the shortest experiment and the most discriminating. A shorter interval gives better results, it could be explained by the listening fatigue. Listening takes a lot of effort and energy. It can make a person extremely tired. The loss of energy makes it difficult to perform well when making the test.

4.4 Quantification of the separability between different age groups using the most discriminating protocol

After the statistical analysis to find the most efficient protocol among all the datasets, univariate analysis is applied to the dataset of the protocol of S-BS for $t_1 = 20s$. The samples

Table 5 Confusion matrix of the classification using RF classifier of S-BS for $t_1 = 20s$ dataset into five age groups

	Child	Teenager	Young adult	Adult	Aged	Omission	Commission
Child	21	1	0	0	0	5%	0%
Teenager	0	25	1	0	0	4%	4%
Young adult	0	0	29	0	0	0%	3%
Adult	0	0	0	40	0	0%	2%
Aged	0	0	0	1	20	5%	0%
Correctly classified	21	25	29	40	20		
Total	21	26	30	41	20		
Overall accuracy	**86%**						

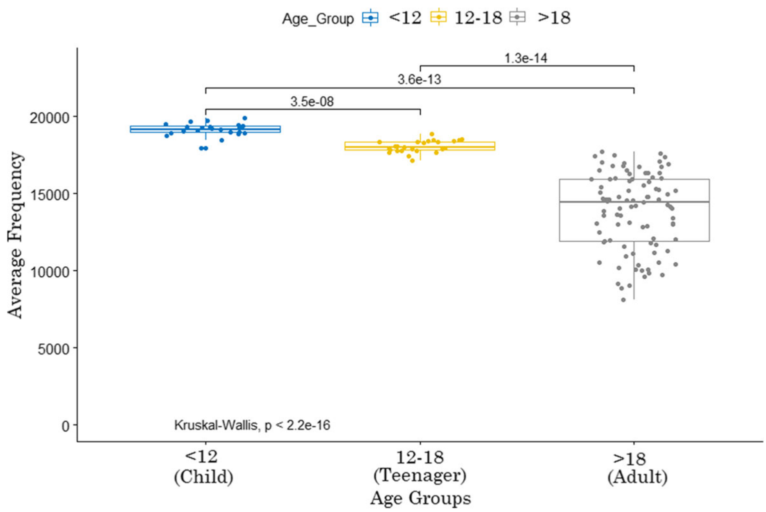

Fig. 10 Boxplot of the data according to the best discriminating protocol of S-BS for $t_1 = 20s$ for three age groups

of the different age groups were systematically compared to one another using univariate T-Tests on the two frequencies of two tests to select those who are showing a statistical difference.

The T-test is based on null hypothesis testing in order to quantify the idea of statistical significance of evidence. A probability value (p-value) is computed to quantify the probability for a given statistical model via a set of random variables. In other words, it measures the size of the difference relative to the variation inside the data samples. In addition to the descriptive interpretation of the separability of the age groups, a graphic interpretation using boxplots is shown in Figs. 10 and 11. The boxplots display variation in samples of the three or five given populations (age groups) and point out the intra and inter-class variability or correlation. The p-value between the three age groups of child, teenager, and adult are inferior to 10^{-8}. Consequently, the three age groups are very different and discriminating according to the hearable frequencies of the volunteers. The distribution of volunteers inside the adult age group is more spread out, it means there is big variability inside this group.

Dividing this age group into three groups shows, according to the p-value of the T-test that the five age groups are also different and well separated. The p-value is also below 10^{-8}. The distribution of the samples of the adult age group is the most dispersed, and the data of young adult and aged groups is confused. It is also the case of the samples of the young adult age group, some samples can be misclassified as adult samples. Consequently, despite the outlier's samples, the p-value is a matter-of-fact that the estimation of age is possible using the auditory perception.

4.5 Age estimation based on the auditory perception

The performances of the regression analysis for age estimation using different machine learning models are summarized in Table 6. In fact, RF regression using 10-fold cross-validation shows the best rate of efficiency with the smallest root mean square of error (RMSE) of 2.6 years for S-BS for $t_1 = 20s$ dataset. The resultant model is stable, and the

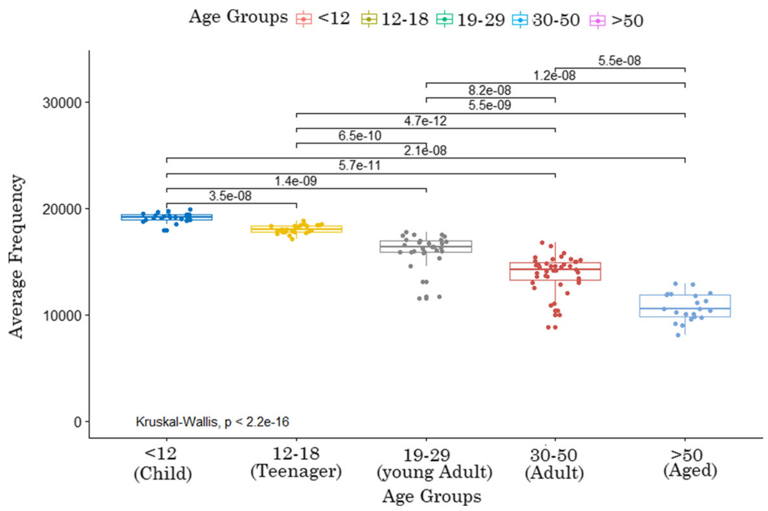

Fig. 11 Boxplot of the data according to the best discriminating protocol of S-BS for $t_1 = 20s$ for five age groups

spread out of the estimated ages from their average value is small, SVR,LR,PR,RR and ANNs show lower accuracy than RF for S-BS for $t_1 = 20s$ dataset. Therefore, the regression model built using Regression Forests in 10-fold cross-validation is the most accurate approach for age estimation using the auditory perception.

Furthermore, the current proposal is sensitive to attacks of users who try to spoof the system about their age. Considering the fact, we created an anti-spoofing system to overcome the problem of vulnerability and enhance the performance of our proposed system [21].

4.6 Comparison with others existing approaches of age classification and estimation

In Tables 7 and 8 present, respectively, the evaluation and comparison results for age classification and estimation. For age groups classification, the existing approaches shown in Table 7 are extracted from published papers [12, 24, 28, 29, 52–54]. Our approach that

Table 6 Performances of the age estimation

Dataset	RF	SVR	LR	PR	RR	ANN's
Speaker						
S-BS(20s)	2.6	6.6	8.1	7.7	5.5	6.0
S-BS(40s)	2.8	6.7	9.2	7.5	6.0	5.9
S-BS(60s)	3.5	5.8	7.3	7.0	6.0	5.8
Headphone						
H-BS	3.1	5.5	9.2	6.3	6.0	6.8
H-RS	3.8	6.9	9.0	7.0	7.0	7.9
H-LS	3.2	5.8	9.1	7.1	7.8	5.03

Table 7 Performance comparison of several approaches of age groups classification

	Ref	Age classification				
Age groups		2	3	4	5	7
Face	[12, 28]	98%				66.6%
Voice	[24]					27% to 54%
	[29]				≅ 70%	
Gait	[45]			80.4%		
	[46]				91:02%	
Keystroke	[53]	72%		64%		
	[25]	84%				
	[54]	≅ 90%				
Auditory Perception	our approach		**92%**		**86%**	

is based on the auditory perception obtains the best results for age classification as compared to the approaches based on face, voice and keystroke. As shown in Table 8, with our approach a significantly smaller mean absolute error of age estimation than the existing approaches based on face [24, 40], voice [29], gait [26, 31, 41] and DNA [13, 36] is obtained. Finally, and importantly, this result clearly evidences that the auditory perception leads to much better age classification and estimation than existing biometric approaches.

Table 8 Performance comparison of several approaches of age estimation

	Ref	Mean Absolute Error (Years)	
Face	[28]	Sex-Age-fusion(SAF)	2.97
		Sex-Age-fusion(SAF)	3.92
	[52]	TSN	2.85
	[24]	MLP	3.64
		Human	5
	[11]	DCNNs	2.74
	[48]	DRFs	2.74
	[40]	DEX	5.84
Voice	[29]		4.7 to 10
Gait	[31]		8.2
	[57]	ODR-GLCNN	5.12
	[41]	Male	5.84
	[41]	Female	6.23
	[26]		6.78
DNA	[13]		4
	[59]		$\pm$ 5.089
	[36]		$\pm$ 4
Auditory perception	our approach		**2.6**

4.7 Performance evaluation

To evaluate the performance of the auditory perception-based age group classification system, we used ten-fold cross-validation using several machine learning techniques. In each round of cross-validation, 90% of the data were randomly selected as training data, and the remaining 10% of the data is used as the testing data to test whether the trained classifier can predict the hearing loss of a subject that corresponds to a specific age group. To assess the performance of the system, two matrices are considered true positive rates and true negative rates. In addition, AUC, defined as the area under a receiver operating characteristic (ROC) curve, which measures the overall classification performances of RF classifier. Three age groups, as shown in Fig. 12, all the subjects in each age group are well classified. The model is performing very well If the value of AUC is closer to 1. In our case, we got 0.92, 0.86, and 0.95. Consequently, each group is well separated and quite well classified, and teenager groups have some misclassification responses.

Similarly, the ROC curve for five age groups (child, teenager, young adult, adult, and aged) using the RF classifier is shown in Fig. 13. The value of AUC for the five age groups using RF classifier is between 0.72-0.95. Even by increasing the number of age groups, the system still can separate the different age groups very well as per the auditory perception responses.

4.8 Discussion

The proposed auditory perception-based approach for human age estimation and classification shows promising results. On the other hand, the vulnerability of the system [22] to spoof attack should be considered, and more robust auditory perception has been considered. The proposed human age estimation system is vulnerable to spoofing such that a subject can easily fool the system:

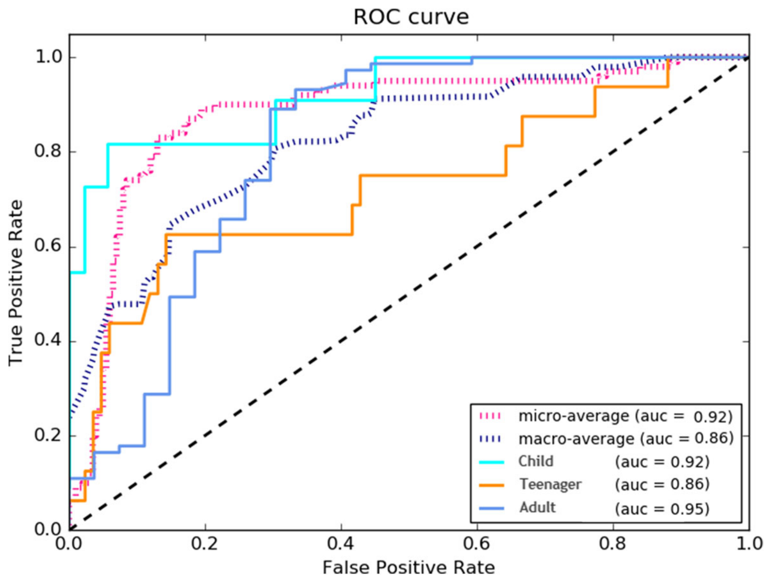

Fig. 12 ROC curve for three age groups (child, teenager, and adult)

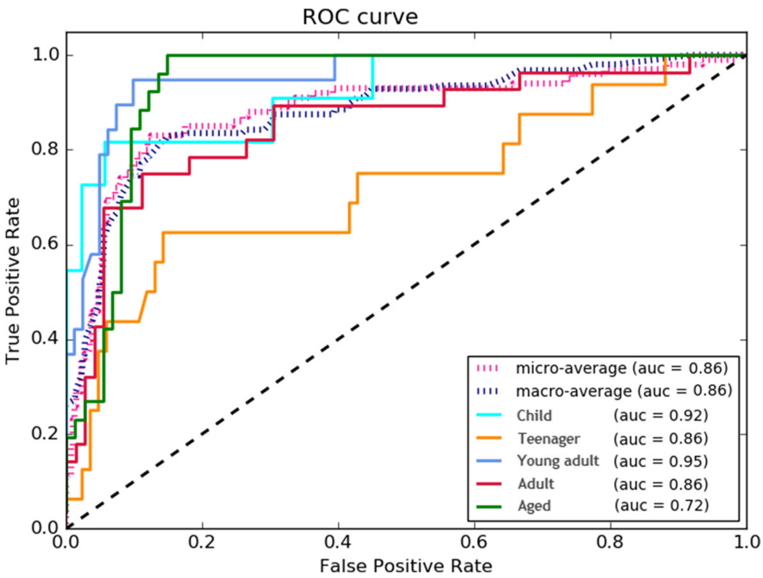

Fig. 13 ROC curves of different age groups. The ROC curve of an ideal classifier should be passing three points: the origin (0, 0), the top-right corner (1, 1) and the top-left corner(0, 1). The ROC curve of a random-guess classifier is just a straight line connecting the origin (0, 0) and the top-right corner(1, 1). The red curve, produced by the proposed RF, is the closest to the ideal curve

- An old subject can impersonate himself as a young one, just by finishing the experiment with a high-frequency in the first test and respond after some seconds as the second test of the experiment.
- A young subject can impersonate himself as an old one, by finishing the first test with lower-frequency, and respond with a higher delay for the second test.

For this reason, an anti-spoofing system based on auditory perception is also developed to enhance the performance of the proposed system [21]. The proposed framework can be applied in real-life applications of biometrics and biomedical. One of the applications could control access filter. It can help to limit the access of adult users to a forum specially designed for kids, or on the other hand, it can be used to limit the access of kids to a forum specially designed for adults. Replacing CAPTCHA can also be a biometric application, as the users are tired of these conventional methods of proving themselves as a human, not a robot. In the field of biomedical, an application can be designed for the detection of hearing loss based on auditory perception-based responses. Every human has a specific threshold of hearing according to his age. As the proposed system is accurately estimating the age of a subject, we also experienced some outliers. Those outliers later checked clinical equipment's such as tuning fork test and audiogram, the result was different, and they were diagnosed with a severe hearing loss. A computer-aided system created for this reason, which can calculate the gap between the real age and estimated age, can be an indicator of hearing loss [20]. Thus, a computer-aided system based on auditory perception for prediction of hearing loss can be developed.

5 Conclusion and future work

In this paper, a new study is introduced about forensic age classification, and estimation based on the auditory perception is presented. The first protocol S-BS for $t_1 = 20s$ is shown the most discriminating, and the Random Forest classifier is the most accurate for age classification and estimation. Using this protocol and this classifier, a good classification rate of 92% and 86% are achieved for three and five age groups, respectively. A robust regression model is also built, and it has accuracy with a root mean square of error of 2.6 years.

To improve our approach, developing more advanced and more comfortable protocols and increasing the dataset to build more robust tools for age classification and estimation will be considered. Another perspective will be to use the age-based auditory perception to analyze the potential attacks in order to develop high-performance anti-spoofing biometric systems. This perspective can overcome the vulnerabilities of future biometric applications based on age estimation with auditory perception.

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