University of Zagreb

Faculty of Organization and Informatics

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TWO-DIMENSIONAL FACE IMAGE CLASSIFICATION FOR DISTINGUISHING CHILDREN FROM ADULTS BASED ON ANTHROPOMETRY

DOCTORAL THESIS

Varaždin, 2015.

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Thesis adviser: Full Professor Bača Miroslav, PhD

Varaždin, 2015.

Sveučilište u Zagrebu

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Petra Grd

KLASIFIKACIJA DVODIMENZIONALNIH SLIKA LICA ZA RAZLIKOVANJE DJECE OD ODRASLIH OSOBA NA TEMELJU ANTROPOMETRIJE

DOKTORSKA DISERTACIJA

Varaždin, 2015.

ABSTRACT

Classification of face images can be done in various ways. This research uses two-dimensional photographs of people's faces to detect children in images. Algorithm for classification of images into children and adults is developed and existing algorithms are analysed. This algorithm will also be used for age estimation. Through analysis of the state of the art research on facial landmarks for age estimation and combination with changes that occur in human face morphology during growth and aging, facial landmarks needed for age classification and estimation of humans are identified. Algorithm is based on ratios of Euclidean distances between those landmarks. Based on these ratios, children can be detected and age can be estimated.

Keywords: Biometrics, face aging, anthropometric ratios, craniofacial morphology, face changes

SAŽETAK

Slike lica mogu biti klasificirane na različite načine. Ovo istraživanje koristi dvodimenzionalne fotografije ljudskih lica za detekciju djece na slikama. Kreiran je novi algoritam za klasifikaciju fotografija ljudskih lica u dvije grupe, djeca i odrasli. Algoritam će se također koristiti za procjenu dobi osoba na slici te će biti analizirani postojeći algoritmi. Kroz analizu literature o karakterističnim točkama korištenih u procjeni dobi i kombinacijom dobivenih karakterističnih točaka s morfološkim promjenama tokom odrastanja i starenja, definirane su karakteristične točke potrebne za klasifikaciju i procjenu dobi. Algoritam se bazira na omjerima Euklidskih udaljenosti između identificiranih karakterističnih točaka.

Ključne riječi: Biometrija, starenje lica, antropometrijski omjeri, kraniofacijalna morfologija, promjene na licu

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List of Abbreviations

MAE - Mean Absolute Error

CS - Cumulative Score

NN - Neural Network

AGES - Agging Pattern Subspace

CDLPP - Class Distance Weighted Locality Preserving Projection

PCA - Principal Component Analysis

LPP - Locality Preserving Projection

HMM - Hidden Markov Model

PFA - Probabilistic Fusion Approach

SVR - Support Vector Regression

SVM - Support Vector Machines

ICA - Independent Component Analysis

AAM - Active Appearance Model

LAR - Least Angle Regression

LDA - Linear Discriminant Analysis

LTP - Local Ternary Patterns

MTWGP - Multi-Task Warped Gaussian Process

EBIF - Enhanced Biologically Inspired Features

BIF - Biologically Inspired Features

ASM - Active Shape Model

RBF - Radial Basis Function

HOG - Histogram of Oriented Gradients

CCA - Canonical Correlation Analysis

MPCA - Multilinear Principal Component Analysis

OHRANK - Ordinal Hyperplane Ranking

NMF - Non-negative Matrix Factorization

SFM - Supervised Facial Model

PLS-R - Partial Least Squares Regression

CAM - Contourlet Appearance Model

NSCT - Nonsubsampled Contourlet Transform

GLOH - Gradient Location and Orientation Histogram

MTL - Multi-task Learning

DCT - Discrete Cosine Transform

OLS-R -Orthogonal Least Square Regression

MFA - Multilinear Subspace Analysis

MFOR - Multi-feature Ordinal Ranking

SRC - Sparse Representation-based Classification

DFT - Discrete Fourier Transform

GP - Gaussian Process

TP - T process

CPNN - Conditional Probability Neural Network

ART - Adaptive Resonance Network

KDE - Kernel Density Estimate

LAG - Lie Algebrized Gaussians

GMM - Gaussian Mixture Models

ACM - Active Contour Model

MLP - Multilayer Perceptron

kNN - K Nearest Neighbours

OLPP - Age Manifold

ALR - Age Group Specific Linear Regression

SFM - Supervised Facial Model

ML-SVM - Multi-label Support Vector Machines

MTSVR - Multi-task Support Vector Regression

GC - Global Classification

LCC - Local Classification

LBPKDE - Local Binary Pattern Kernel Density Estimate

CM - Craniofacial Morphology

AM - ANthropometric Model

EM - Expectation-Maximization

HH - Highest point of the head

MFL - Middle point of the forhead (left)

PHL - Most protruded point of the head (left)

MPL - Midpoint between PHL and LAML

LAML - Most lateral point at the angle of the mandible (left)

PMTL - Protrusion of the mental tubercle (left)

LMLC - Lowest point in the midline on the lower border of the chin

PMTR - Protrusion of the mental tubercle (right)

LAMR - Most lateral point at the angle of the mandible (right)

MLP - Midpoint between LAMR and PHR

PHR - Most protruded point of the head (right)

MFR - Middle point of the forhead (right)

LEBL - Most lateral point of the eyebrow (left)

HUMEL - Highest point on the upper margin of the midline portion of the eyebrow (left)

MBHML - Midpoint between HUMEL and MHEL (left)

MHEL - Medial hinge of the eyebrow (left)

LEL - Lateral hinge of the eyelid (left)

HEL - Highest point of the eyelid (left)

MPEL - Middle point of the eye (left)

LMLEL - Lowest point in the middle of the margin of the lower eyelid (left)

MEL - Medial hinge of the eyelid (left)

LPMEL - Lowest point in the middle of eyesocket (left)

MNS - Midpoint of the nasofrontal suture

FMN - Point of the nose where forhead meets the nose

MHER - Medial hinge of the eyebrow (right)

MBHMR - Midpoint between HUMER and MHER (right)

HUMER - Highest point on the upper margin of the midline portion of the eyebrow (right)

LEBR - Most lateral point of the eyebrow (right)

LER - Lateral hinge of the eyelid (right)

HER - Highest point of the eyelid (right)

MPER - Middle point of the eye (right)

LMLER - Lowest point in the middle of the margin of lower eyelid (right)

MER - Medial hinge of the eyelid (right)

LPMER - Lowest point in the middle of eyesocket (right)

NB - Nose bridge

MBNP - Midpoint between NB and PNT

MUNAL - Most upper point of the nasal ala (left)

MUNAR - Most upper point of the nasal ala (right)

MNAOL - Medial point of the nasal ala outer margin (left)

PNT - Most protruded point of the nasal tip

MNAOR - Medial point of the nasal ala outer margin (right)

LNAL - Most lateral point of the nasal ala (left)

LNAR - Most lateral point of the nasal ala (right)

LNL - Most lateral point of the nose (left)

LNAIL - Lowest lateral point of the nasal ala inner margin (left)

INTUL - Most inner point between the nose tip and upper lip

LNAIR - Lowest lateral point of the nasal ala inner margin (right)

LNR - Most lateral point of the nose (right)

HULR - Highest point of the upper lip (right)

MVUL - The midpoint of the vermilion border of the upper lip

HULL - Highest point of the upper lip (left)

LULML - Most lateral point where the upper and the lower lip meet (left)

MULLM - Midline point where upper and lower lip meet

LULMR - Most lateral point where the upper and the lower lip meet (right)

MLLL - Midpoint of the lower margin of the lower lip

MPLL - Midpoint of the pogonion and lower lip

AC - Most anterior point of the chin

ANN - Artificial Neural Network

ID - Identifier of the subject

IM_ID - Image identifier

IM_AGE - Age of subject in image

DOB - Date of birth

DOA - Date of Acquisition

ECRM - Electronic Customer Relationship Management

List of Appendixes

Chapter 1: Introduction

Age estimation and age classification of humans using their face images are a part of a field of biometric. Biometric systems use bihevioral and physiological characteristics to recognize individuals. Soft biometric traits like age, gender, ethnicity, height, weight in combination with hard biometric traits can be used to enhance the performance of biometric systems. This research concentrates on age classification and estimation.

Age estimation is an important task in classifying face images. It can be defined as the determination of the age of the person or his/her age group (Scholarpedia, 2013), (Grd, 2013). Human age classification and estimation can be defined in many ways, but this research is concerned with the age estimation and classification based on two-dimensional images of people's faces. Age estimation and classification is done using face anthropometry.

For the purposes of this research definitions of basic terms are given. Age classification is used to classify images in those of children and adults. Children are defined as people from age 0 to 17 and adults are defined as people from age 18 and above. Age estimation in this research is defined as determining the age of a person based on biometric features, more precise on the basis of two-dimensional images of human face (Scholarpedia, 2013). Facial landmarks can be defined as the standard reference points on the face used by scientists to recognize the face, or in this case, predict the age of a person (Face and Emotion, 2013). Anthropometry is the science dealing with measurements of the size, weight, and proportions of the human body (Medical Dictionary, 2015). Therefore, facial anthropometry deals with measurements of the size and proportions of human face.

The aging process affects the structure and appearance of face in many ways. The changes that occur are related to facial morphology, and changes in the face texture. Some characteristics of facial morphology appear only in people of a certain age and change during the aging process (Koruga, Bača and Schatten, 2011). Changes in skin texture usually occur in adulthood. According to Geng, Fu and Smith-Miles (2010) changes in the face that occur during aging and growth are: chin becomes more prominent, cheeks spread over a larger area, facial characteristics increase and cover the interstitial spaces, head falls backwards, reducing the free space on the surface of the skull, facial hair becomes thicker and changes color, skin color changes, skin becomes thinner, darker, less elastic and more leathery, wrinkles appear, underchin appears, cheeks sag and bags under the eyes appear. Based on all these changes, the age of a person can be determined.

The main motivation of this research is to create an algorithm for classification of humans into minors and adults, for use in detecting illegal content, especially for detection of potential paedophile images. This research will identify the characteristic points of the face necessary to classify face images, it will identify the most appropriate model for age estimation, private database with normalized facial images will be created and a new algorithm for age classification will be developed. Accuracy of the algorithm will be calculated and compared with the accuracy of existing algorithms.

The scientific contribution of this research is as follows:

- Systematization of knowledge on age classification,
- Identification of facial landmarks relevant for age classification and estimation,
- A novel data mining based approach for ratios identification that are important for the age classification and estimation processes
- Creation of a new algorithm for age classification,
- Evaluation of anthropometric model on a large database.

In addition to scientific, this research has a social contribution also. Human age estimation is widely applicable and has great potential: determining the age of immigrants or asylum seekers in situations where there are no documents proving the age of the person, for websites where entrance is allowed only for persons over the age of 18, in order to improve the system for face recognition (most of them are sensitive to changes during aging), searching for missing persons over the years, in human-computer interaction based on age, for the purpose of predicting a persons aging, in the fight against pedophilia (removing images of minors from various portals or personal computers), etc. These are just some of the possible uses of human age estimation, and with further development of new technologies, there will be more.

The second chapter of the thesis gives a literature review of the field of biometric age estimation and classification. A systematic review of state of the art research is done and an overview of research papers is given. Next, the papers are categorized according to face representations model and aging function learning methods. After that, a description of the most often used face representation models and aging function learning methods, along with their advantages and disadvantages is given. In this chapter, changes on human face during growth and aging are identified. Chapter three describes the new algorithm for age classification and estimation. The algorithm is divided into two parts: face representation and classification. First, facial landmarks needed for ratios calculation are identified. These ratios are used for face representation. After that, the neural network, more accurately a multi layer perceptron, as a classification method is described. Chapter four describes experimental results. This chapter is divided into three parts. First part is a description of databases used for algorithm training and testing. The second part is performance measurement where the hypotheses have been confirmed. The last part of this chapter compares the new algorithm results with existing algorithms. Chapter five describes the possible applications of the algorithm and in conclusion overview of the research, answers to the research questions and confirmed hypotheses are given.

1.1. Objective and Hypotheses

The main objective of this research is to develop an algorithm for human age classification and estimation which can classify humans into minors and adults. This new algorithm will be based on the model proposed in this research.

More specific objectives, to be achieved in order to realize the main objective are:

- Identify changes on the face that occur during growth and aging
- Identify facial landmarks necessary for algorithm creation
- Identify ratios needed for the new algorithm

- Create a new age estimation algorithm
- Compare the new algorithm accuracy with the accuracy of existing algorithms

Based on the defined goals, the research questions are set:

RESEARCH QUESTION 1

What changes occur on human face during growth and aging?

RESEARCH QUESTION 2

Which facial landmarks are important for age classification and estimation?

RESEARCH QUESTION 3

Which facial ratios are important for age classification and estimation?

Other than research questions there are two hypothesis:

HYPOTHESIS 1

The newly developed algorithm distinguishes children from adults based on facial anthropometric ratios with an accuracy of more than 80% when used on the publicly available Fg-net database.

HYPOTHESIS 2

Usage of different facial anthropometric ratios than those used in existing anthropometric model, increases the accuracy of the algorithm when used for age estimation.

1.2. Methodology

This research combines both qualitative and quantitative methods, which means that it uses a combined research design. According to Creswell (2008), combined research design is useful when neither qualitative nor quantitative approach separately are not suitable to best understand the research problem, or when the power of qualitative and quantitative research together can offer the best understanding of the problem. More specifically, in this study, it is first necessary to identify changes in human face during growth and aging, then it is necessary to identify facial landmarks needed to describe these changes. Regarding to the applicability of research, this research is an applied research because it relates to the acquisition of new knowledge for the purpose of finding practical solutions for immediate application (Tkalec Verčić, Sinčić Ćorić and Pološki Vokić, 2010).

The first step of this research will be a review of scientific literature on human age estimation on the basis of two-dimensional images of the face. For this purpose following scientific methods will be used (Kulenović and Slišković, 2015):

- Description is used in the initial phase of this research. It is a simple way of describing facts, objects, processes and connections between them without scientific interpretation
- Compilation is overtaking others' results of scientific research, their observations, opinions and conclusions.
- Analysis is the breakdown of complex thought creations to their simpler component parts and study each part separately and in relation to other parts.
- Synthesis is connecting simple creations to complex thought, linking them together and parts are connected to each other.
- Generalization takes individual observations and draws generalized conclusions.
- Specialization takes a general idea and comes up with a new idea, narrower in scope and richer in content.

This is followed by one of the most important steps, and that is collecting data for the research. This step is divided into two parts. The first part is listing, analysis and acquisition of existing and publicly available databases of face images. The only database publicly available and appropriate for this research is Fg-net (Fg-net, 2014) face database containing 1002 images of 82 different people with marked age. In addition to the aforementioned database private face database will be created. All participants whose photos are collected to create this database are informed about the purpose for which the images will be used, the personal data protection law, the privacy policy on the protection of personal data and they signed the consent for the use of their personal data in this research. Once the images are collected, they have to be normalized, which means that the images need to be reviewed, all images have to be face images, and they have to be larger than the minimum size defined.

The next step is to define the differences in the structure of the human face during growth and aging. Literature on human face changes will be consulted in this step. To this end, the methods of comparison and generalization will be used:

- Comparison is comparing the same or related facts, phenomena, processes or relationships, and establishing their similarities and differences.
- Generalization derives generalized conclusions from observations in the previous step.

After this, it is easy to define changes on human face during growth and aging and facial landmarks relevant for age estimation. The method that will be used for this is abstraction. Abstraction is a thought process that separates irrelevant and highlights important element or traits of specific objects or phenomena research, or in this case, separate the important from the unimportant facial landmarks (Kulenović and Slišković, 2015).

After the previous steps, it is necessary to develop an algorithm for age classification. The basis of the algorithm are ratios on human face. It needs to be determined which face ratios are important. To this end, non-linear correlation will be used. Spearman coefficient will determine the correlation between each ratio and human age. After that, the algorithm needs to be implemented using programming languages (Python). After the implementation of the algorithm, it needs to be tested. There are various algorithms for facial landmark detection, but manual detection is still the most accurate so manually selected facial landmarks will be used as algorithm input. The algorithm gives a class value and age estimate as outputs. To evaluate the classification part of the algorithm confusion matrix will be created and accuracy, precision, recall and specificity will be calculated. Accuracy is the proportion of the total number of predictions that were correct. Precision is the proportion of positive cases that were correctly identified. Recall is the proportion of actual positive cases which are correctly identified. Specificity is the proportion of negative cases that were correctly identified. To evaluate estimation part of the algorithm, the output from the algorithm (estimated age) is compared to real age of a person (chronological age). Measures that are commonly used in literature to evaluate the performance of the age estimation algorithms are Mean Absolute Error (MAE) and Cumulative Score (CS) (Geng, Zhou and Smith-Miles, 2007), (Guo et al., 2008), (Lanitis, Taylor and Cootes, 2002), (Lanitis, Draganova and Christodoulou, 2004). MAE is defined as the average absolute error between the estimated and chronological age (Guo et al., 2008). CS shows the percentage of cases in the test set where the estimated age error is less than the threshold. Based on the above measures algorithm accuracy will be assessed.

At the end of the research, the analysis and interpretation of results will be done, and conclusions will be given. For this, various tables and diagrams will be used.

1.3. Ethical Aspects

In this research, personal data are collected and processed. Collection and processing of such data has to be in accordance with the Croatian Law on Personal Data Protection (Narodne Novine, 2013).

During data collection, respondent was aware of the fact that he/she is giving personal information, aware of the purpose for which the information is collected, and that they can withdraw their data at any time.

Respondent received a Privacy policy for review, which describes the duration of the Privacy policy, all the data collected, the purpose for which the data is collected, and whom to contact in case of any questions. In addition to this policy, all participants signed a statement of consent, with which they give their consent for use of their personal data for this research, and confirm that they received the Privacy policy mentioned earlier. Since this research collects personal data of minors, their parents/guardians gave consent for the use of their data.

Chapter 2: Literature Review

In order to better position this research, review of existing papers on age estimation algorithms is given.

First algorithm for human age estimation was proposed by Kwon and Lobo (1994). They proposed a theory and practical calculation for the age classification of face images. Their calculations are based on the craniofacial morphology of the person and wrinkle analysis. They distinguish between primary and secondary facial characteristics, and during the implementation of the theory they first use the primary characteristics of the face (eyes, nose, mouth, chin, top of the head and the left and right ends of the head), and then the secondary. From primary characteristic ratios are calculated based on which humans are classified into three classes (children, young adults and older adults). In the analysis of secondary characteristics wrinkle map is used for detection and measurement of wrinkles on the face. By combining the analysis of ratios of the primary characteristics and analysis of facial wrinkles, images are classified in the above mentioned three classes.

Horng, Lee and Chen (2001) propose a system which classifies humans into four classes: babies, young adults, middle-aged adults and old adults. Facial features are obtained using a Sobel edge operator and two back-propagation neural networks are used to classify images into age groups. The first neural network uses the geometric features to distinguish whether the facial image is a baby. If it is not, then the second network uses the wrinkle features to classify the image into one of three adult groups. The identification rate achieves the accuracy of 90.52% for the training images and 81.58% for the test images.

Lanitis, Draganova and Christodoulou (2004) describe the performance of different classifiers for age estimation. Classifiers used are based on quadratic functions, a shortest distance classifier and neural network based classifier. They were evaluated using single step classification method and hierarchical age estimation approach. According to their results, hierarchical age estimation based on quadratic function and neural networks achieves better age estimation results. The authors also recognize that for algorithm improvement, fine details of the face need to be taken into consideration for age estimation.

Kalamani and Balasubramanie (2006) apply the fuzzy lattice neural network for age classification of humans into six age groups: tiny tots, blooming buds, brimming youth, midsummer dreamers, steady goers and senior citizens. Nine features are used for this classification, all of them are wrinkle features. The main difference between this approach and the earlier ones is that each image belongs to every group with a certain degree. The resulting group is the one where the image has a maximum degree.

Geng, Zhou and Smith-Miles (2007) presented aging pattern subspace (AGES) method for age estimation. The basic idea is to model the aging pattern, which is defined as a sequence of images sorted chronologically, by constructing a representative subspace. The proper aging pattern for a previously unseen face is determined by the projection in the subspace that can reconstruct the face image with minimal error, while the position of the face image in that aging pattern indicate age.

Another important research is one by Fu, Xu and Huang (2007) who classify existing methods for age estimation into three categories: anthropometric model, aging pattern subspace and age regression. They develop a new framework for age estimation which integrates three modules: face detection, manifold learning and multiple linear regression. Using age manifold a lower-dimensional representation of the image is obtained, and age estimation is defined as the problem of multiple linear regression in the manifold space.

Ueki et al. (2008) compare their Class Distance Weighted Locality Preserving Projection (CDLPP) method for dimensionality reduction for age estimation with most often used methods: Principal Component Analysis (PCA), Locality Preserving Projection (LPP) and Locality Preserving Projection with Local Scaling. The method is based on the extension of LPP method by adding weights to the data with close class labels.

Zhuang et al. (2008) propose using a patch-based Hidden Markov Model (HMM) supervector for face image patches representation. This way, they capture the spatial structure of human faces and loosen the assumption of identical face patch distribution. Euclidean distance is used as a similarity measurement.

Shen and Ji (2008) propose a geometric feature based age classification system. This system classifies images into two age groups: babies and adults. They also developed an algorithm for eyes, nose and mouth location invariant to pose, background and illumination. The problem with this algorithm is that it uses only one ratio (eye-eye distance and eye-nose distance), and if a subject looks down or up the algorithm is not accurate.

Ben, Su and Wu (2008) use the fact that different facial regions mature at different ages, and use the most significant region for facial age estimation. Their framework consists of two steps: age range prediction and usage of selected region in the predicted age range to make final age estimation.

Guo et al. (2008) say that current age estimation approaches are still not good enough for practical application. In their paper they present age manifold learning scheme for facial aging characteristics extraction, and they design a locally adjusted robust regressor for learning and age estimation. Their approach improves the accuracy with respect to other methods. The same authors (Guo et al., 2008) propose another algorithm for human age estimation based on facial images. The Probabilistic Fusion Approach (PFA) framework fuses a regressor and a classifier. It is derived based on the conditioned Bayes' rule, and by transforming the Support Vector Regression (SVR) and Support Vector Machines (SVM) outputs to probabilities, a serial probabilistic fusion scheme has been developed. This method yields better results than all the previous methods.

Suo et al. (2008) say that the key point in age estimation is defining the feature set essential to age perception. For that reason, they built a hierarchical face model for faces appearing at low, middle and high resolution.

Qi and Zhang (2009) developed an age classification system that automatically separates kid faces from adult faces in real time. The system consists of three steps: face detection, face normalization and age classification. They use Independent Component Analysis (ICA) to extract local facial features and SVM to train the age classifier.

Geng and Smith-Miles (2009) propose an age estimation method based on multilinear subspace analysis where the aging images are organized in a third-order tensor without pre-assumptions.

Guo et al. (2009) investigated bio-inspired features for facial age estimation. First step is the extraction of biologically inspired features, then feature dimension reduction using PCA and statistical learning for age estimation, and the last step is the estimated age output using SVM.

Ricanek et al. (2009) developed the first multi-ethnic age estimator. They used Active Appearance Model (AAM) to capture aging features, Least Angle Regression (LAR) for dimensionality reduction and SVR for function modeling. The age estimation framework consists of five modules: face detection, face encoding, feature selection using LAR, model fitting using SVR and age estimation.

Long (2009) proposes a new framework where age is predicted based on the learned metric as opposed to Euclidean distance used in most research. Unlike the manifold learning, which is nonlinear, in this framework a full metric is learned and expressed as a linear transformation, which makes it easy to project novel data into it.

Research by Gao and Ai (2009) refers to the use of Gabor filters and fuzzy Linear Discriminant Analysis (LDA) method for the classification of humans in four groups: baby, child, adult and elderly. The paper gives a mathematical basis of belonging to groups.

Luu et al. (2009) present a new technique for age estimation that combines the AAM and SVM to improve the accuracy of age estimation.

Turaga, Biswas and Chellapa (2010) describe the role of geometric attributes on human face, described by a set of facial landmarks for age estimation. They also show that the landmark space can be interpreted as a Grassmann manifold.

Chen et al. (2010) propose age classification of people based on facial image into three groups: children, adults and the elderly. After face detection, face is extracted and 52 characteristic points are located. These characteristic points are used to build the AAM model. Texture characteristics are sent to the SVM to estimate the age group.

Luu et al. (2010) proposed an age estimation technique that combines holistic and local facial features. Holistic features are AAM linear encoding of each face, and local features are extracted using Local Ternary Patterns (LTP). They use these features to classify faces into one of two age groups.

Zhang and Yeung (2010) proposed a multi-task warped Gaussian process (MTWGP) based on a variant of the Gaussian process called warped gaussian process. As authors state, unlike previous age estimation methods which need to specify the form of the regression functions or determine many parameters in the functions, the form of the regression functions in MTWGP is implicitly defined by the kernel function and all its model parameters can be learned from data automatically.

The most accurate algorithm up to date is the Enhanced Bio-Inspired Features (EBIF) by El Dib and El-Saban (2010). They extend the algorithm based on biologically inspired features (BIF) by adding fine detailed facial features, automatic initialization using Active Shape Model (ASM) and analyzing the complete facial area (including forehead).

Zhai, Qing and Ji-Xiang (2010) use improved non-negative matrix factorization algorithm to obtain a linear represenatation of data under non-negativity constrains. This algorithm avoids the singularity of within-class scatter matrix, and solves the small samples problem of LDA. For age prediction a Radial Basis Function (RBF) neural network has been used.

Duong et al. (2011) propose an advanced approach for age estimation by combining global and local characteristics derived from face images. AAM technique is used to construct the global characteristics of the face, while the local facial characteristics are obtained by Local Binary Patterns (LBP) coding, and SVR is used to train the initial and refined aging function.

Hajizadeh and Ebrahimnezhad (2011) propose a new algorithm to classify people according to age using Histogram of Oriented Gradients (HOG) for description of the face. Their method classifies subjects into four different age groups. The system is divided into three main parts: pre-processing, feature extraction and classification in the age group.

Lu and Tan (2011) proposed a novel method for age estimation by using multiple feature fusion via facial image analysis. They fused shape and texture informatioin of the same image by the Canonical Correlation Analysis (CCA). Multiple linear regression function with a quadratic model was used for age estimation.

Selvi and Vani (2011) developed a system for age estimation of a person in three steps: face detection, extraction of characteristic points and age estimation. In their system age estimation is carried out using Multilinear Principal Component Analysis (MPCA).

Chang, Chen and Hung (2011) propose a new algorithm for age estimation - Ordinal Hyperplane Ranking (OHRank). The algorithm design is based on the relative order of age information. Each ordinal hyperplane separates all the facial images into two groups depending on the relative order and price sensitivity. They convert the age estimation problem into a series of K subproblems of binary classifications according to the ordering property.

Zhan, Li and Ogunbona (2011) extend the Non-negative Matrix Factorization (NMF) to learn a localized non-overlapping subspace representation for age estimation. One individual extended NMF subspace is learned for each age or age group. The age is estimated based on its reconstruction error after being projected into the learned age subspaces.

Chen et al. (2011) studied age estimation in a multiethnic environment using 39 combinations of four feature normalization methods, two simple feature fusion methods, two feature selection methods and three face representation methods (Gabor, AAM and LBP). The results of the research were that Gabor outperforms AAM and LBP with single face representation.

Nkengne, Tenenhaus and Fertil (2011) used a Supervised Facial Model (SFM) for age estimation. SFM combines shape model and texture model information. These two models are combined using Partial Least Squares Regression (PLS-R) to build the SFM.

Yang et al. (2011) proposed a feature fusion method to estimate the face age via SVR. SVR uses global features from AAM and local features from Gabor wavelet transformation. First they perform AAM on the image to get global features and shape-free image, then they do a Gabor wavelet transformation on that shape-free image and get Gabor feature representation. They employ PCA to reduce the dimensionality of Gabor representation. After that, they did a regression analysis on AAM features and Gabor features to estimate the age of a face.

Luo et al. (2011) in order to improve the accuracy of age estimation, proposed applying Multi-Label Learning to the age features. They treat each facial image as an example associated with the origin label as well as its neighbouring ages. Their results show that this approach outperforms single-label approaches.

Luu et al. (2011) propose a facial landmarks localization method which is more accurate and faster than AAM. Their Contourlet Appearance Model (CAM) doesn't only extract global information, but also local texture information using the Nonsubsampled Contourlet Transform (NSCT). They apply this model to face age estimation, and get more accurate results.

Liang et al. (2011) base their method on Gradient Location and Orientation Histogram (GLOH) descriptor and Multi-task Learning (MTL). They use GLOH to get age related local and spatial information, and MTL is used to select the most informative GLOH bins for age estimation. The corresponding weights are determined by ridge regression. The important thing in this approach is that it decreases the computation time because of reduced dimensionality.

Choi et al. (2011) proposed a new age estimation method combining global and local facial features and a hierarchical classifier. They propose a new extraction methods for wrinkles and skin and a new hierarchical method for age estimation. Region specific Gabor filter is used to extract wrinkle features, and LBP is used to extract skin features. The hierarchical age estimation is designed to overlap the age classes to reduce classification errors of the boundary data.

Guo, Liou and Nguyen (2011) in their research combine shape feature, texture feature and frequency feature using Active Shape Model (ASM), Radon transform and Discrete Cosine Transform (DCT) to get robust hybrid features for classification. They use SVM for hierarchical classification.

Kohli, Prakash and Gupta (2011) use AAM and ensemble of classifiers for age estimation. They extract features from face images using AAM and then ise a global classifier to distinguish between child/teen-hood and adulthood, before age estimation. After that they use different aging functions to model the aging process.

Li et al. (2012) propose a new method for age estimation based on ordinal discriminative feature learning. The idea is to preserve local manifold structure, but also to keep ordinal information among aging faces. They also try to remove redundant information from locality information and ordinal information by minimizing nonlinear correlation and rank correlation.

Cao et al. (2012) base their research on the premise that face images from the same age vary too much to estimate the age accurately. First step is that rank relationships of ages is learned from various face images, then the age is estimated based on those rank relationships and the age information of a reference set. They use Gabor features for face representation.

Lu and Tan (2012) propose an ordinary preserving manifold analysis for facial age estimation to find a low-dimensional subspace so that the samples with similar label values are projected to be as close as possible, and those with different label values as far as possible. They applied ordinary preserving manifolds to LDA and Multilinear Subspace Analysis (MFA).

Li et al. (2012) look at age estimation as a problem of distance-based ordinal regression, where facial aging trend can be discovered by a learned distance metric. Using this metric, both ordinal information of age groups and local geometry structure of target neighbourhoods can be preserved.

Gao (2012) bases his research on the fact that the high variability of aging patterns and the sparsity of available data present challenges for model training. Instead of training one global aging function, he trains an individual function for each person using a multi-task learning approach. He also proposes a similarity measure for clustering these aging functions. This algorithm is called Clustered Multi-task Support Vector Regression Machine.

Weng et al. (2012) propose a Multi-feature Ordinal Ranking (MFOR) method for facial age estimation. They formulate the problem of face age estimation as a group of ordinal ranking subproblems, and each of these subproblems derives a separating hyperplane to divide face instances into two groups: age larger than k and age not larger than k. They construct multiple ordinal ranking models, each coresponding to a feature set and aggregate them into an age estimator.

Li, Wang and Zhang (2012) propose a hierarchical framework for age estimation using weighted and OHRanked Sparse Representation-based Classification. Because of the similar aging features of humans of the same age, Sparse Representation-based Classification (SRC) can be used. Adding weights and OHRank improves the results of the algorithm.

Kou, Du and Zhai (2012) combine global and local facial features for age estimation. They extract these features by using Discrete Fourier Transform (DFT) and PCA.

Zhang (2012) uses Gaussian Process (GP) and T Process (TP) for age estimation. In this method, the form of regression function is defined by kernel function and almost all parameters can be learnt automatically from the data using efficient gradient methods.

Yin and Geng (2012) propose a Conditional Probability Neural Network (CPNN), a new label distribution learning algorithm for facial age estimation. CPNN is a three layer neural network whose inputs are both the target variable and conditional feature vector, and the output is the conditional probability of the target variable given the feature vector.

Nithyashri and Kulanthaivel (2012) use wavelet transform to extract facial features. Then they calculate the Euclidean distances between each of the features. These values become inputs into Adaptive Resonance Network (ART). The output of this network is the age group (child, adolescence, adult, senior adult).

Kilinc and Akgul (2013) use the fusion of geometric and texturale features for facial age estimation. They first calculate the probability that face image belongs to each overlapping age group. After that, an interpolation based technique is used for final age estimation.

Ylioinas et al. (2013) use Kernel Density Estimate (KDE) for facial representation and SVR for age estimation. The important aspect of their algorithm is its computational lightness and algorithmic simplicity.

Chao, Liu and Ding (2013) combine distance metric learning and dimensionality reduction to explore the connection between facial features and age labels. They exploit the intrinsic ordinal relationship among human ages and overcome the data imbalance problem. Also, they present an age-oriented local regression to capture the aging process.

Gunay and Nabiyev (2013) propose a method based on Radon features. This method consists of four modules: preprocessing, feature extraction with radon transform, dimensionality reduction with PCA and age estimation with multiple linear regression.

Hu et al. (2013) propose a new discriminative feature Lie Algebrized Gaussians (LAG). They built LAG on Gaussian Mixture Models (GMM) and it can capture the aging manifold of an image by preserving the Lie group manifold structure information embedded in the feature space. The age estimation is done in two steps. The first step is to obtaine an adaptive age group for each image, and the second step is to learn a local classifier from selected age classes to determine the final age.

An overview of state of the art research according to feature extraction method and age estimation method can be seen in Table 2.1. Methods used in state of the art age classification and estimation algorithms.

Table 2.1. Methods used in state of the art age classification and estimation algorithms

Algorithm	Feature extraction method	Age estimation method	Estimation	Classification (Number of classes)
Kwon and Lobo (1994)	Active Contour Model	-	No	Yes (3)
Horng, Lee and Chen (2001)	Sobel Edge Detector	Back Propagation Neural Networks	No	Yes (4)
Lanitis, Draganova and Christodoulou (2004)	Principal Component Analysis	Quadratic Function Shortest Distance Multilayer Perceptron Self-Organizing Map	Yes	No
Kalamani and Balasubramanie (2006)	Sobel Edge Detector	Fuzzy Lattice Neural Network	No	Yes (6)
Geng, Zhou and Smith-Miles (2007)	Active Appearance Model	Aging Pattern Subspace	Yes	No
Fu, Xu and Huang (2007)	Age Manifold	Regression Model Fitting	Yes	No
Ueki et al. (2008)	Class Distance Weighted Locality Preserving Projection	K Nearest Neighbours	Yes	No
Zhuang et al. (2008)	Patch-based Hidden Markov Model	Nearest Centroid Classifier	Yes	No
Shen and Ji (2008)	Sobel Edge Detector Haar-like Features	Gaussian Modeling Based Classification	No	Yes (2)
Ben, Su and Wu (2008)	Active Appearance Model	Linear Aging Function	Yes	No
Guo et al. (2008)	Age Manifold	Locally Adjusted Robust Regression Function	Yes	No
Guo et al. (2008)	Active Appearance Model	Support Vector Machine and Support Vector Regression	Yes	No

Suo et al. (2008)	Active Appearance Model and Hierarchical Face Model	Age Group Specific Linear Regression, Multi-layer Perceptron, Support Vector Regression and Logistic Regression	Yes	No
Qi and Zhang (2009)	Independent Component Analysis and Principal Component Analysis	Support Vector Machine	No	Yes (2)
Geng and Smith-Miles (2009)	Active Appearance Model	Multilinear Subspace Analysis	Yes	No
Guo et al. (2009)	Principal Component Analysis	Support Vector Machine and Support Vector Regression	Yes	No
Ricanek et al. (2009)	Active Appearance Model and Least Angle Regression	Support Vector Regression	Yes	No
Long (2009)	Active Appearance Model	Metric Learning	Yes	No
Gao and Ai (2009)	Gabor Feature			
Luu et al. (2009)	Active Appearance Model	Support Vector Machine and Support Vector Regression	Yes	No
Turaga, Biswas and Chellapa (2010)	Active Appearance Model	Support Vector Machine, Support Vector Regression and Ridge Regression	Yes	No
Chen et al. (2010)				
Luu et al. (2010)	Active Appearance Model and Local Ternary Patterns	Support Vector Machine and Support Vector Regression	Yes	No
Zhang and Yeung (2010)		Multi-Task Warped Gaussian Process	Yes	No
El Dib and Saban (2010)	Active Shape Model and Gabor	RBF Support Vector Regression	Yes	No

		and Support Vector Machine		
Zhai, Qing and Ji-Xiang (2010)	Improved Non-negative Matrix Factorization	Radial Basis Function	Yes	No
Duong et al. (2011)	Active Appearance Model and Local Binary Pattern	Support Vector Regression	Yes	No
Hajizedah and Ebrahimnezhad (2011)	Histogram of Oriented Gradients	K Nearest Neighbour	No	Yes (4)
Lu and Tan (2011)	Manual and Canonical Correlation Analysis	Quadratic Function	Yes	No
Selvi and Vani (2011)	Gabor Filter	Multilinear Principal Component Analysis	Yes	No
Chang, Chen and Hung (2011)	Active Appearance Model	Ordinal Hyperplane Ranking	Yes	No
Zhan, Li and Ogunbona (2011)	Extended Non-negative Matrix Factorization	Coarse to fine	Yes	Yes (4)
Chen et al. (2011)	Gabor, Active Appearance Model, Principal Component Analysis	Support Vector Regression	Yes	No
Nkengne, Tenenhaus and Fertil (2011)	Partial Least Squares Regression	Supervised Facial Model	Yes	No
Yang et al. (2011)	Active Appearance Model and Gabor	Support Vector Regression	Yes	No
Luo et al. (2011)	Multi-task Learning	Multi-label - Support Vector Machine	Yes	No
Luu et al. (2011)	Contourlet Appearance Model	Support Vector Regression and Support Vector Machine with Radial Basis Function	Yes	No

Lian et al. (2011)	Gradient Location and Orientation Histogram	Support Vector Regression and Ridge regressor	Yes	No
Choi et al. (2011)	Manual, Gabor and Local Binary Pattern	Support Vector Machine and Support Vector Regression	Yes	No
Guo, Liou and Nguyen (2011)	Active Shape Model, Radon and Discrete Cosine Transform	Support Vector Machine and Support Vector Regression	Yes	No
Kohli, Prakash and Gupta (2011)	Active Appearance Model	Classifiers based on different disimilarities	Yes	No
Li et al. (2012)	Preserving Locality and Ordinal Information	Ordinal Hyperplane Ranking	Yes	Yes (7)
Cao et al. (2012)	Gabor	Ranking Support Vector Machine	Yes	No
Lu and Tan (2012)	Linear Discriminant Analysis and Multilinear Subspace Analysis	Ordinary Preserving Manifold Analysis	Yes	No
Li et al. (2012)	Active Appearance Model	K Nearest Neighbour Regression Model	Yes	No
Gao (2012)	Active Appearance Model	Multi-task Support Vector Regression	Yes	No
Weng et al. (2012)	Active Appearance Model and Biologicaly Inspired Features	Multi-feature Ordinal Ranking	Yes	No
Li, Wang and Zhang (2012)	Active Appearance Model, Active Shape Model and Local Binary Pattern	Sparse Representation-based Classification	Yes	No
Kou, Du and Zhai (2012)	Discrete Fourier Transform and Principal Component Analysis	Global and Local Classification	Yes	No

Zhang (2012)	Active Appearance Model	Gaussian Process and T Process	Yes	No
Yin and Geng (2012)	Active Appearance Model	Conditional Probability Neural Network	Yes	No
Nithyashri and Kulanthaivel (2012)	Wavelet Transformation	Adaptive Resonance Network	No	Yes (4)
Kilinc and Akgul (2013)	Local Binary Pattern, Gabor	AdaBoost	Yes	No
Ylioinas et al. (2013)	Local Binary Pattern Kernel Density Estimate	Support Vector Regression	Yes	No
Chao, Liu and Ding (2013)	Active Appearance Model	K Nearest Neighbour - Support Vector Regression	Yes	No
Gunay and Nabiyev (2013)	Radon and Principal Component Analysis	Multiple Linear Regression	Yes	No
Hu et al. (2013)	Lie Algebrized Gaussians	Improved Hierarchical Estimation	Yes	No

According to literature review, changes in texture of human face (skin changes, wrinkles, skin elasticity etc.) are mostly influenced by external factors and are individual and change from person to person. Since in this research, global age estimation is considered, these changes are not appropriate. Also, in nowadays makeup has become an important factor in every day life for most women, and some men which influences the age estimation systems based on changes in texture of the face (Chen, Dantcheva and Ross, 2014). Other than this, more and more people use plastic surgery, botox or some other way to remove wrinkles and aging effects on their faces. This also influences age estimation systems. If an age estimation system with good accuracy, based only on facial shape changes, was to be developed, it would be a great improvement in this field.

Table 2.2. State of the art papers by sources

Name of the source	**No. of papers**
IC on Automatic Face and Gesture Recognition	2
IC on Computer Vision and Pattern Recognition	3
IC on Biometrics: Theory, Applications and Systems	3
IC on Image Processing	2
IC on Pattern Recognition	3
Transactions on Pattern Analysis and Machine Intelligence	1
IC on Intelligent Computing	4
Computer Society Conference on Computer Vision and Pattern Recognition	3
IC on Acoustics, Speech and Signal Processing	4
IC on Control, Automation, Robotics and Vision	1
IC on Machine Learning and Cybernetics	1
IC on Multimedia and Expo	1
Pattern Recognition	2
Transactions on Image Processing	1
Transactions on Systems, Man and Cybernetics	2
IC on Biometrics	2
IC on System Science and Engineering	2
ISNN	2
Multimedia Tools Application	1

Computer and Information Sciences	1
IC on Advanced Computing	1
IC on Image Analysis and Processing	1
IC on Intelligent Systems Design and Applications	1
IC on Recent Trends in Information Technology	1
IS on Biomedical Imaging: From Nano to Macro	1
International Workshop on Multimedia Signal Processing	1
Iranian Machine Vision and Image Processing	1
Pacific-Asia Conference on knowledge Discovery and Data Mining	1
Tamkang Journal of Science and Engineering	1
IC on Computer Graphics, Imaging and Visualization	1
Advances in Biometrics	1
Chinese Conference on Biometric Recognition	4
International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications	1
Multimedia Tools and Applications	1

It can be seen in Table 2.2. State of the art papers by sources, that most of the papers on age estimation algorithms were published in conference proceedings. The conferences are international conferences from different parts of the world, specialized in image processing, computer vision and biometrics, which ensures the quality of research. Also, the largest number of research on age estimation has been published in 2011 as can be seen in Table 2.3. State of the art papers by year of publication.

Table 2.3. State of the art papers by year of publication

Year of publication	**No. of papers**	**Year of publication**	**No. of papers**
2013	5	2007	2
2012	11	2006	1
2011	15	2004	1
2010	6	2001	1
2009	7	1994	1
2008	7		

2.1. Aging Face

Human face goes through different changes during growth and aging. One of the changes during a persons aging process is the change in craniofacial morphology (CM). Different craniofacial characteristics appear at different age and change during the aging process. One of the most important researches in this field is the one conducted by Farkas (1994) and Farkas and Munro (1987). Farkas (1994) took measurements from 57 facial landmarks. There were three kinds of measurements: projective measurements (defined as the shortest distance between two landmarks), tangential measurements (defined as the distance between two landmarks measured along skin surface) and angular measurements. In this research Farkas also identified landmarks that can be estimated from photographs of human faces. According to Ramanathan and Chellapa (2006) only projective measurements can be estimated accurately using photogrammetry of frontal face images. That is the reason this research uses these measurements as its basis.

According to Fu, Guo and Huang (2010) there are two main stages of facial changes. First stage is early growth and development of the face. In this stage the face size is getting larger during the craniofacial growth. Because of that growth, other facial features change also. Forehead slopes back, shrinks and releases spaces on the surface of the cranium. Eyes, ears, nose and mouth expand and cover interstitial spaces. Cheeks extend to larger areas and the chin becomes more protrusive. In this stage, the skin does not change much. The second stage is adult aging, where the most changes are skin aging and changes in texture. There are some changes in shape, but not as big as in the first stage.

Many studies related to CM of individuals from different aspects have been conducted. One of these studies was conducted by Coleman and Grover (2006) which refers to changes in the three-dimensional human face geometry during the aging process. Coleman and Grover conducted their research in terms of plastic surgery, in order to cancel the results of aging. They have focused on adults and unwanted changes on the face during the aging process. Some of the changes they stated, and according to which it is possible to discern the age of people are: reduction in the height of the face, increase in the width and depth of the face, and facial features (nose, chin) become more distinct. They also divide the face into thirds and claim that human beauty is contained in the central part of the face. Ricanek (2008) researched the craniofacial characteristics of aging in terms of building more robust systems for face recognition in biometrics. He provides an overview of changes in facial structure and soft tissues over the years.

Geng, Yun and Smith-Miles (2010) in their work on automatic age estimation recognize two phases of facial aging. The first phase is the early years, defined as the years from birth to adulthood. At this stage, most of the changes are changes in craniofacial growth, as shown in Figure 2.1. Head shape changes caused by craniofacial growth (Geng, Yun and Smith-Miles, 2010):

- Beard becomes more prominent
- Cheeks are spread over a larger area
- Facial characteristics increase and cover the interstitial spaces
- Forehead falls backwards, reducing the free space on the surface of the skull

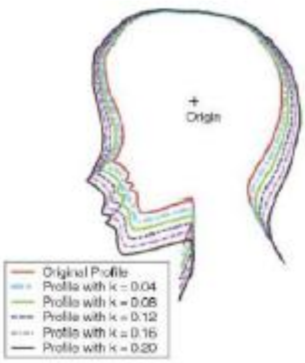

Figure 2.1. Head shape changes caused by craniofacial growth (Geng, Yun and Smith-Miles, 2010)

In addition to changes caused by craniofacial growth, minor skin changes occur (Geng, Yun and Smith-Miles, 2010):

- Facial hair become thicker and change color
- Skin color changes

The second phase of facial aging recognized by Geng, Yun and Smith-Miles (2010) is during adulthood. Adulthood is defined as the time from the end of growth to old age. The main changes in this stage are skin changes. The skin becomes thinner, darker, less elastic and more leathery. Also, there are wrinkles, underchin, cheeks sag and bags under the eyes appear. But there is also some small craniofacial growth at this stage, mainly changes in the shape of the face, but most of craniofacial growth occurs at an early age of the individual, which can be seen in Figure 2.2 Craniofacial changes during growth and aging from Fg-net database.

Figure 2.2. Craniofacial changes during growth and aging from Fg-net database (Fg-net, 2014)

Nakai, Okakura and Arakawa (2010) and Okakura and Arakawa (2011) define five ways in which human face shape changes: the face becomes longer, eyebrow become thicker, eyes become thinner, nose becomes longer and ridge sharper and wings of nose become wider.

To summarize all this research, Table 2.4. Face shape changes caused by growth or aging, gives an overview of changes during growth and aging.

Table 2.4. Face shape changes caused by growth or aging

Paper	**Growth or aging**	**Change**
Fu, Guo and Huang (2010), Geng, Yun and Smith-Miles (2010)	growth	Forehead slopes back, shrinks and releases spaces on the surface of the cranium
Fu, Guo and Huang (2010), Geng, Yun and Smith-Miles (2010)	growth	Eyes, ears, nose and mouth expand and cover interstitial spaces
Fu, Guo and Huang (2010), Geng, Yun and Smith-Miles (2010)	growth	Cheeks extend to larger areas
Fu, Guo and Huang (2010), Geng, Yun and Smith-Miles (2010)	growth	Chin becomes more protrusive

Coleman and Grover (2006)	aging	Reduction in the height of the face
Coleman and Grover (2006)	aging	Increase in the width and depth of the face
Nakai, Okakura and Arakawa (2010), Okakura and Arakawa (2011)	growth	Face becomes longer
Nakai, Okakura and Arakawa (2010), Okakura and Arakawa (2011)	growth	Eyebrows become thicker
Nakai, Okakura and Arakawa (2010), Okakura and Arakawa (2011)	growth	Eyes become thinner
Nakai, Okakura and Arakawa (2010), Okakura and Arakawa (2011)	growth	Nose becomes longer
Nakai, Okakura and Arakawa (2010), Okakura and Arakawa (2011)	growth	Ridge becomes sharper
Nakai, Okakura and Arakawa (2010), Okakura and Arakawa (2011)	growth	Wings of nose become wider

2.2. Types of Age

According to Geng, Yun and Smith-Miles (2010) there are several types of age:

- Chronological age is defined as the number of years a person has lived.
- Appearance age is the age information defined by appearance of the person.
- Perceived age is defined by people based on the appearance of the person.
- Estimated age is an age defined by the computer from the way person a looks.

Appearance age is usually very close to the chronological age. The objective of age estimation is that estimated age is as close to chronological or appearance age as possible.

2.3. Face Representation Models

There are a large number of different face representation models described in the introduction of this chapter. The most important models recognized in literature are (Geng, Yun and Smith-Miles, 2010), (Guo, Fu and Huang, 2009), (Fu, Guo and Huang, 2010), (Guo, 1994):

- Anthropometric Model,
- Active Appearance Model,
- Aging Pattern Subspace,
- Age Manifold,
- Biologically-Inspired Models.

2.3.1. Anthropometric Model

Facial Anthropometry is the science of measuring the size and proportions of the human face (Montagu, 1960).

The main idea of this model is to consult research related to craniofacial growth and development. Craniofacial research theory uses a mathematical model for description of head from birth to adulthood:

$$\Theta' = \Theta,\ R' = R\,(1 + k\,(1 - \cos\Theta)) \qquad (1)$$

where Θ is the angle formed by the vertical axis, R is the radius of the head circle, k is a parameter which increases with time, and (R', Θ') circuit growth over time (Alley, 1998).

Farkas (1994) gave an overview of facial anthropometry. He defined facial anthropometric as measures taken from 57 characteristic points of the face taken over years. For age estimation, distances and ratios between characteristic points are commonly used, instead of using a mathematical model, because it is difficult to measure face profile on the two-dimensional face images (Fu, Guo and Huang, 2010).

Computations in this model are based on the craniofacial development theory. Changes in the appearance of face caused by growth are sufficient to categorize faces in several age groups. This model is suitable for a rough age estimation, but not for detailed classification (Fu, Xu and Huang, 2007). This is the main reason why Kwon and Lobo (1999) used wrinkle analysis to do the separation between young adults and seniors.

The anthropometric model is based on human face ratios, as shown on Figures 2.3 to 2.8.

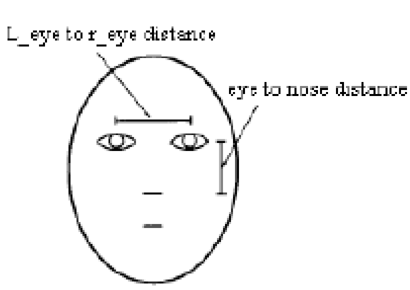

Figure 2.3. Anthropometric ratio 1 on human face (Kwon and Lobo, 1999)

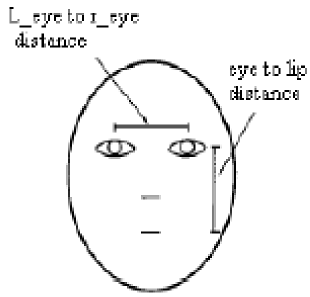

Figure 2.4. Anthropometric ratio 2 on human face (Kwon and Lobo, 1999)

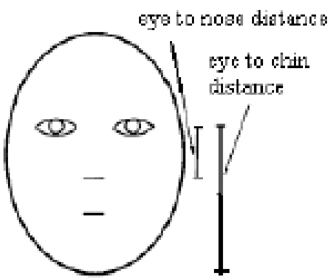

Figure 2.5. Anthropometric ratio 3 on human face (Kwon and Lobo, 1999)

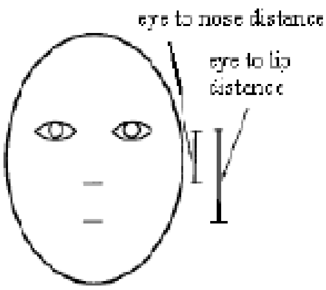

Figure 2.6. Anthropometric ratio 4 on human face (Kwon and Lobo, 1999)

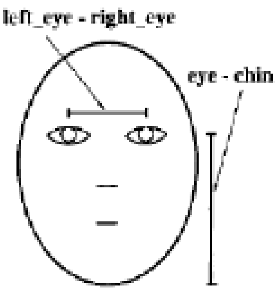

Figure 2.7. Anthropometric ratio 5 on human face (Kwon and Lobo, 1999)

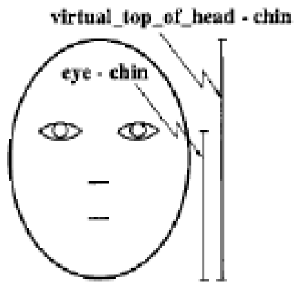

Figure 2.8. Anthropometric ratio 6 on human face (Kwon and Lobo, 1999)

In practice, anthropometric model can only be used for en face images for measuring facial geometry, because the distances and ratios are calculated from two-dimensional images of individuals that are sensitive to the positions (Fu, Guo and Huang, 2010). This model takes into account only geometry of face, without information about the texture.

2.3.2. Active Appearance Model

This model was proposed by Cootes, Edwards and Taylor (1998). Using facial images, statistical shape model and intensity model are learned separately. It is an algorithm for matching a statistical model of object shape and appearance to a new image. They are built during a training phase and by taking advantage of the least squares techniques, it can match to new images easily. The active appearance model is related to the active shape model. One disadvantage of active shape model is that it only uses shape constraints and does not take advantage of all the available information, especially the texture across the target object. This can be modeled using an active appearance model (Cootes, Edwards and Taylor, 1998).

In 2002 The AAM has been expanded to facial aging (Lanitis, Taylor and Cootes, 2002) suggesting an aging function defined by $age = f(b)$, to explain the variation in years. *Age* is the age of a person in the picture, *b* is a vector containing 50 parameters learned from AAM, and *f* is an aging function. The function defines the relationship between person's age and facial description parameters (Fu, Guo and Huang, 2010).

There are different forms of an aging function. Some examples of such functions are: quadratic aging function, linear aging function, cubic aging function and other.

Unlike anthropometric model, AAM is not oriented only to younger people, but deals with assessment of the age of people of all ages. It works in a way that takes into consideration not only the geometry of human face, but its texture also. In this way the age of a person can be estimated more accurately (Fu, Guo and Huang, 2010).

2.3.3. Aging Pattern Subspace

Instead of using every face image separately, aging pattern subspace model uses a sequence of facial aging images to model the aging process. This model was developed by Geng, Zhou and Smith-Miles (2007) and named Aging Pattern Subspace (AGES). Aging pattern is defined as a sequence of facial image of a person, sorted by time.

AGES works in two steps. The first step is a learning step, the second step is the age estimation step (Fu, Guo and Huang, 2010). In the first step, PCA is used to obtain the subspace representation. The difference from the standard PCA approach is that there are probably no images for each year for each aging pattern. So Expectation-Maximization (EM) is used as a method of iterative learning to minimize error in reconstruction. Error while reconstruction is defined as the difference between the available images of the face and the face reconstructed images (Fu, Guo and Huang, 2010). In the second step, the test face image needs to find a pattern of aging that suits that image, and the exact position of the year in the sample. Position year returned is the estimated age of a person in the test image (Fu, Guo and Huang, 2010).

To cope with incomplete data, due to difficulties in data collection, the aging pattern subspace models the sequence of a person’s aging face images by learning subspaces. Age of the person being tested is determined by the projection in the subspace that can best reconstruct the face image (Fu, Xu and Huang, 2007).

Methods based on aging functions view age estimation as a classification problem: face images are data, and the goal is the age of a person in the picture. According to

Geng, Zhou and Smith-Miles (2007) aging pattern is a sequence of images sorted by age.

The emphasis of this model is the use of facial images of a person at different ages to define the aging pattern.

2.3.4. Age Manifold

Instead of learning the specific aging pattern for each person, it is possible to learn the common pattern of aging for more than one person at different ages. For each age, more than one facial image is used for age representation. Each person can have several face images at one age or in an age range (Fu, Guo and Huang, 2010). Therefore, this model is more flexible than AGES model, and it is much easier to collect a larger number of samples (facial images) and create a larger database.

This model uses a manifold embedding technique for learning a low-dimensional aging trend for many facial images of the same age. The only requirement of this model is that the sample size for learning is large enough so that embedded manifold can be taught with statistical sufficiency (Fu and Huang, 2008).

2.3.5. Biologically-Inspired Models

One of the most accurate age estimation algorithms to date is the EBIF algorithm based on biologically inspired models. The idea for biologically inspired model (BIF) came from human vision system. It showed good results in object recognition, so Guo et al. (2009) adapted this model to human age estimation based on face images. In object category recognition, prototypes are randomly selected from learning images and stored for template matching in S2 units (Guo, 1994). Guo et al. (2009) found that these features from pre-learned prototypes do not do well in age estimation, so they proposed a new model that has S1 and C1 units and a STD operation in C1 feature extraction (Guo, 1994).

BIF can deal with small changes in rotation, scale and image translation, so it is good to combine BIFs with manifold learning which is sensitive to image alignment (Guo, 1994).

2.3.6. Discussion

Each of the described models has its advantages and disadvantages. The overview of these characteristics can be seen in Table 2.5. Advantages and disadvantages of face representation models.

Table 2.5. Advantages and disadvantages of face representation models

Model	**Advantages**	**Disadvantages**
Anthropometric Model	Useful for age group classification Useful for younger people age estimation	Considers shape only Sensitive to head poses
Active Appearance Model	Considers shape and texture Deals with any age Robust against head poses	Has problems with incomplete data
Aging Pattern Subspace	Copes with incomplete data	Learning aging pattern for each person separatly Hard to collect sufficent data
Age Manifold	More flexible Easier to collect data	Sensitive to image alignment
Biologically Inspired Model	Deals with changes in rotation, scale and alignment	

Since anthropometric model is the only model that separates facial texture from facial ratios and is specialized in age classification of young people, this model is chosen for facial representation. Also, anthropometric model has not yet been evaluated on a large database so this is another contribution to the field of age estimation.

2.4. Aging Function Learning Methods

All of the research on age estimation can be grouped in (Guo et al., 2009): multiclass classification problem, regression problem and hybrid approach as a combination of these two (Figure 2.9. Classification of aging function learning method).

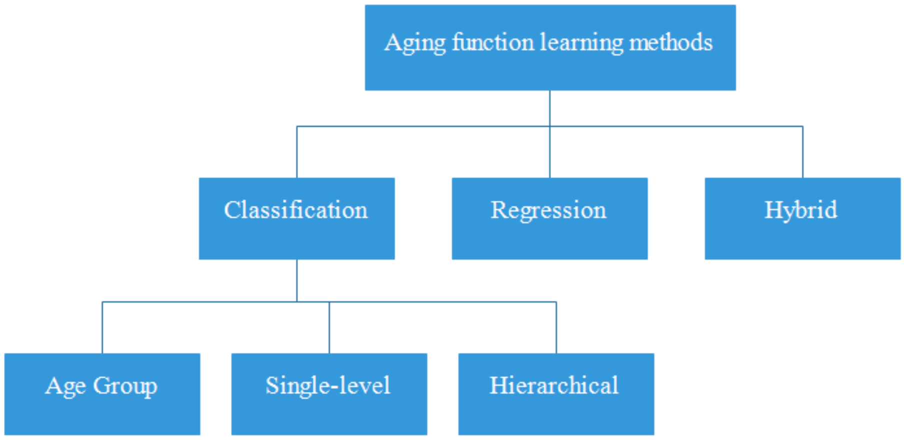

Figure 2.9. Classification of aging function learning methods

2.4.1. Classification

If age estimation is viewed as a classification problem each age label is treated as a single class (Fu, Guo and Huang, 2010). There are a large number of classifiers used in age estimation (Guo, 1994), (Choi et al., 2011):

- Artificial Neural Networks
- Support Vector Machines
- Nearest Neighbour
- Quadratic function
- Fuzzy Linear Discriminant Analysis
- Hierarchical estimation
- Support Vector Regression
- Multilayer Perceptron

Some of the researchers who have studied the problem of age estimation as a classification problem are Lanitis, Draganova and Christodoulou (2004), Guo et al. (2008), Ueki, Hayashida and Kobayashi (2006) and many other.

Age classification can further be divided into three approaches (Choi et al., 2011): Classification into age groups, single-level age estimation or hierarchical age etimation.

Age group classification is an approach that roughly estimates the age group. It is suitable for coarse classification, but it is not so good for detailed age estimation. Single-level and hierarchical age estimation focus on a detailed assessment of the age. Single-level age estimation finds age label in full dataset using a single estimator (Choi et al., 2011). Hierarchical age estimate is rough-fine method for finding age labels in a smaller data set. First, age group in which an image belongs to is estimated. Then, based on the age group, detailed age is estimated. It improves the performance by considering the differences of age feature values according to age group. If there is an error in age group estimation step it transfers to detailed age estimation step (Choi et al., 2011).

2.4.2. Regression

There is another way in which age estimation can be observed. Age is a sequential set of values and the age estimation can be viewed as a regression problem (Fu, Guo and Huang, 2010).

Regressors used for age estimation (Guo, 1994):

- Quadratic Function
- Multiple Linear Regressor
- Support Vector Regression
- Semi-definite Programming Technique
- Expectation-Maximization
- Robust Multi-instance Regression
- Least Angle Regression

Age estimation as a regression problem has been researched by Lanitis, Draganova and Christodoulou (2004), Fu, Xu and Huang (2007), Yan et al. (2007), Zhou et al. (2005), Ni, Song and Yan (2009) and other.

2.4.3. Hybrid

The third view is a hybrid approach. This approach raises the question of which of the above approaches is better to estimate the age (Fu, Guo and Huang, 2010). Some of the researchers compared the above approaches on multiple databases. For example, Guo et al. (2008) concluded that SVM performs better on YGA database, and SVR performs better on Fg-net database. So there is no universal conclusion which is better because it depends on the database used.

Chapter 3: New Algorithm for Age Classification

There are a lot of problems in age classification and estimation and this is why it's such a challenging field of research. One major problem is the lack of quality images, and since the research involves minors, there is a problem of collecting photographs of minors. Other constraint is the correct facial landmark determination. There are various algorithms for facial landmark detection, but manual detection is still the most accurate.

All of the algorithms in previous research have two basic steps: feature extraction and classification. In the newly developed algorithm in this research, facial landmarks are manually selected and they serve as an input to the algorithm. Classification in the algorithm is done using multilayer perceptron. An overview of the algorithm is shown as a block diagram in Figure 3.1. Block diagram of the new algorithm.

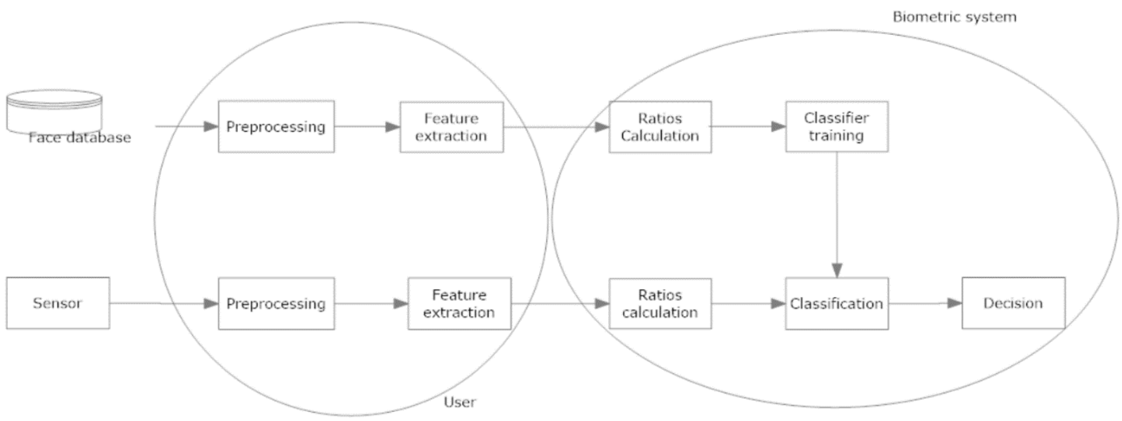

Figure 3.1. Block diagram of the new algorithm

3.1. Face Representation

As explained in previous chapters, there are many face representation models used in literature. This research uses anthropometric model as a starting point. Next chapters describe facial landmarks and ratios used for age classification and estimation in this algorithm.

3.1.1. *Facial Landmarks*

In order to calculate the ratios on human face, important facial landmarks need to be selected. Next six images show facial landmarks used for age estimation by different authors (Figure 3.2. to Figure 3.7.).

Figure 3.2. Landmark points as identified by Kleinberg and Siebert (2012)

Figure 3.3. Landmark points as identified by Takimoto et al. (2007)

Figure 3.4. Landmark points as identified by Txia and Huang (2009)

Figure 3.5. Landmark points as identified by Ramanathan and Chellapa (2006)

Figure 3.6. Landmark points as identified by Kostinger et al. (2011)

Figure 3.7. Landmark points as identified by Izadpanhi and Toygar (2012)

Based on literature analysed, 57 facial landmark points are defined. From all landmarks used in previous researches, landmarks used at least two times are selected as relevant in this research. All of these landmark points are shown in Figure 3.8. All landmark points as identified in literature. The abbreviations of the landmarks and their names are shown in Table 3.1. Landmark points identified in literature

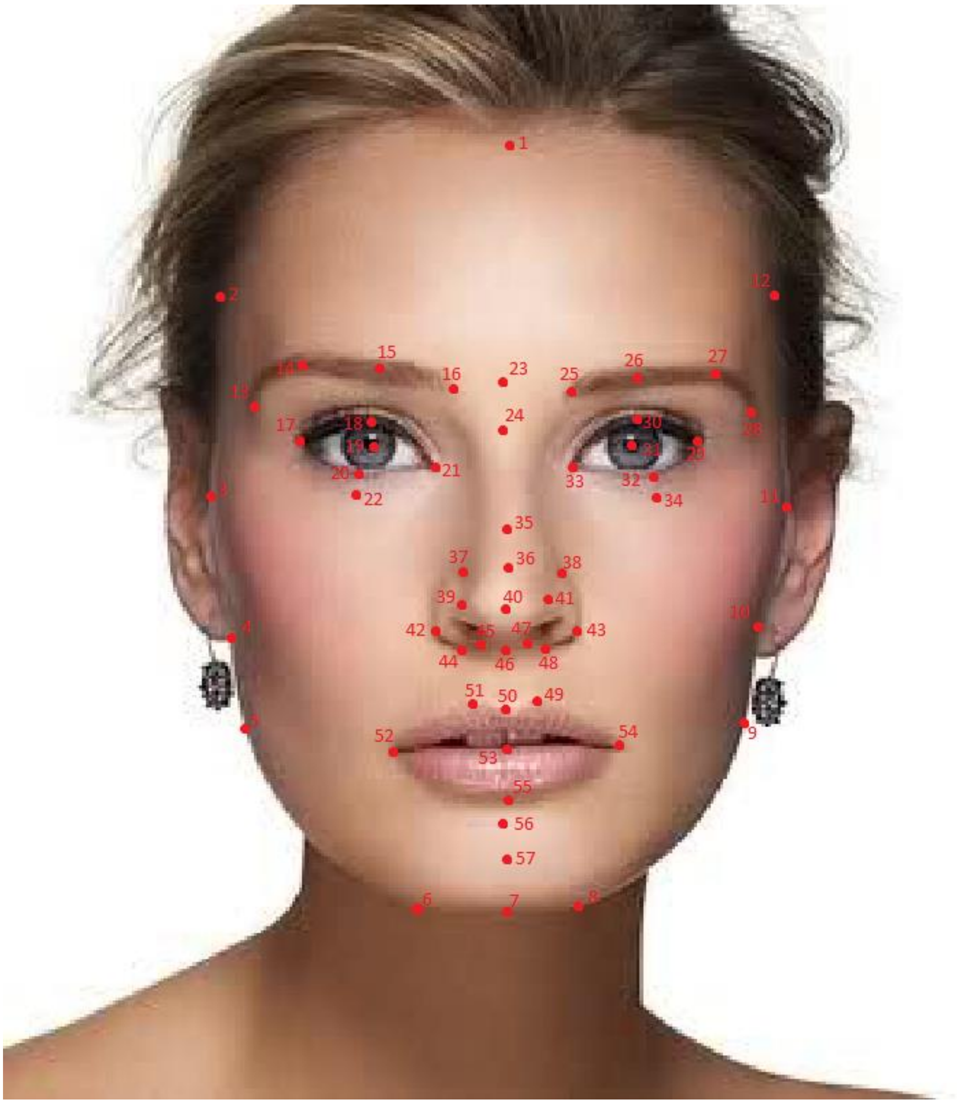

Figure 3.8. All landmark points as identified in literature

Table 3.1. Landmark points identified in literature

No.	Abbreviation	Description
1	HH	Highest point of the head
2	MFL	Middle point of the forhead (left)
3	PHL	Most protruded point of the head (left)
4	MPL	Midpoint between PHL and LAML
5	LAML	Most lateral point at the angle of the mandible (left)
6	PMTL	Protrusion of the mental tubercle (left)
7	LMLC	Lowest point in the midline on the lower border of the chin
8	PMTR	Protrusion of the mental tubercle (right)
9	LAMR	Most lateral point at the angle of the mandible (right)
10	MLP	Midpoint between LAMR and PHR

11	PHR	Most protruded point of the head (right)
12	MFR	Middle point of the forhead (right)
13	LEBL	Most lateral point of the eyebrow (left)
14	HUMEL	Highest point on the upper margin of the midline portion of the eyebrow (left)
15	MBHML	Midpoint between HUMEL and MHEL (left)
16	MHEL	Medial hinge of the eyebrow (left)
17	LEL	Lateral hinge of the eyelid (left)
18	HEL	Highest point of the eyelid (left)
19	MPEL	Middle point of the eye (left)
20	LMLEL	Lowest point in the middle of the margin of the lower eyelid (left)
21	MEL	Medial hinge of the eyelid (left)
22	LPMEL	Lowest point in the middle of eyesocket (left)
23	MNS	Midpoint of the nasofrontal suture
24	FMN	Point of the nose where forhead meets the nose
25	MHER	Medial hinge of the eyebrow (right)
26	MBHMR	Midpoint between HUMER and MHER (right)
27	HUMER	Highest point on the upper margin of the midline portion of the eyebrow (right)
28	LEBR	Most lateral point of the eyebrow (right)
29	LER	Lateral hinge of the eyelid (right)
30	HER	Highest point of the eyelid (right)
31	MPER	Middle point of the eye (right)
32	LMLER	Lowest point in the middle of the margin of lower eyelid (right)
33	MER	Medial hinge of the eyelid (right)
34	LPMER	Lowest point in the middle of eyesocket (right)
35	NB	Nose bridge
36	MBNP	Midpoint between NB and PNT
37	MUNAL	Most upper point of the nasal ala (left)
38	MUNAR	Most upper point of the nasal ala (right)
39	MNAOL	Medial point of the nasal ala outer margin (left)
40	PNT	Most protruded point of the nasal tip
41	MNAOR	Medial point of the nasal ala outer margin (right)
42	LNAL	Most lateral point of the nasal ala (left)
43	LNAR	Most lateral point of the nasal ala (right)
44	LNL	Most lateral point of the nose (left)
45	LNAIL	Lowest lateral point of the nasal ala inner margin(left)
46	INTUL	Most inner point between the nose tip and upper lip
47	LNAIR	Lowest lateral point of the nasal ala inner margin(right)
48	LNR	Most lateral point of the nose (right)
49	HULR	Highest point of the upper lip (right)

50	MVUL	The midpoint of the vermilion border of the upper lip
51	HULL	Highest point of the upper lip (left)
52	LULML	Most lateral point where the upper and the lower lip meet (left)
53	MULLM	Midline point where upper and lower lip meet
54	LULMR	Most lateral point where the upper and the lower lip meet (right)
55	MLLL	Midpoint of the lower margin of the lower lip
56	MPLL	Midpoint of the pogonion and lower lip
57	AC	Most anterior point of the chin

If changes that happen during facial growth and aging are taken into consideration, some of these landmarks can be ommited. The second step of purification occurs and new set of landmarks is defined (Figure 3.9. Landmark points used in this research and Table 3.2. Landmark points used in this research).

Figure 3.9. Landmark points used in this research

Table 3.2. Landmark points used in this research

No.	Abbreviation	Description
1	HH	Highest point of the head
2	MFL	Middle point of the forhead (left)
3	PHL	Most protruded point of the head (left)
5	LAML	Most lateral point at the angle of the mandible (left)
7	LMLC	Lowest point in the midline on the lower border of the chin
9	LAMR	Most lateral point at the angle of the mandible (right)
11	PHR	Most protruded point of the head (right)
12	MFR	Middle point of the forhead (right)
17	LEL	Lateral hinge of the eyelid (left)
18	HEL	Highest point of the eyelid (left)
20	LMLEL	Lowest point in the middle of the margin of the lower eyelid (left)
21	MEL	Medial hinge of the eyelid (left)
24	FMN	Point of the nose where forhead meets the nose
29	LER	Lateral hinge of the eyelid (right)
30	HER	Highest point of the eyelid (right)
32	LMLER	Lowest point in the middle of the margin of lower eyelid (right)
33	MER	Medial hinge of the eyelid (right)
40	PNT	Most protruded point of the nasal tip
43	LNAR	Most lateral point of the nasal ala (right)
46	INTUL	Most inner point between the nose tip and upper lip
49	HULR	Highest point of the upper lip (right)
51	HULL	Highest point of the upper lip (left)
53	MULLM	Midline point where upper and lower lip meet
54	LULMR	Most lateral point where the upper and the lower lip meet (right)
55	MLLL	Midpoint of the lower margin of the lower lip
56	MPLL	Midpoint of the pogonion and lower lip

In the end, there are 26 facial landmarks used in this research. As it was mentioned earlier, facial landmarks are detected manually. To this end, a Python script that records mouse click positions was created.

Landmark_anotation.py

```
import os
import Tkinter
import Image, ImageTk

root=Tkinter.Tk()
def button_click_exit_mainloop (event):
    event.widget.quit()
```

```
    logfile=open("landmarks.csv", "a")
    logfile.write("\n")

def callback(event):
    logfile=open("landmarks.csv", "a")
    logfile.write(str(event.x))
    logfile.write(";")
    logfile.write(str(event.y))
    logfile.write(";")

root.bind("<Button-2>", button_click_exit_mainloop)
root.bind("<Button-1>", callback)
root.geometry('+%d+%d' % (200,200))
dirlist=os.listdir(".")
old_label_image=None
for f in dirlist:
        try:
                logfile=open("landmarks.csv", "a")
                logfile.write(str(f))
                images=Image.open(f)
                root.geometry('%dx%d' % (images.size[0],images.size[1]))
                tkpi=ImageTk.PhotoImage(images)
                label_image=Tkinter.Label(root, image=tkpi)
                label_image.place(x=0,y=0,width=images.size[0],height=images.size[1])
                root.title(f)
                if old_label_image is not None:
                        old_label_image.destroy()
                old_label_image=label_image
                root.mainloop()
        except:
                pass
logfile.close("landmarks.csv")
```

Input to the script is an image, and output is a file with coordinates of selected landmarks (landmarks.csv). This file is later saved as *fg-net_coordinates.xlsx*.

3.1.2. Ratios

After defining facial landmarks important for age estimation, important ratios need to be defined. In this research, important ratios are defined based on statistical analysis of correlation between all ratios on human face and age of a person.

In order to define these ratios, Euclidean distances between specific landmarks need to be calculated using the formula for Euclidean distance (2).

If A and B are points in two-dimensional space with coordinates (x_1, y_1) and (x_2, y_2) respectively, Euclidean distance between those two points is defined as

$$d(A,B) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}. \qquad (2)$$

All possible distances between facial landmarks (d_n) are calculated using the formula for number of diagonals of an *n* sided polygon and adding the number of sides of a polygon (Artrea, 2015):

$$d_n = \frac{n(n-3)}{2} + n \qquad (3)$$

There are 325 possible distances on human face based on previously determined facial landmarks.

Next step is to define ratios important for age estimation. First, all possible ratios are calculated. Number of ratios is calculated by:

$$NPR\ (Number\ of\ Possible\ Ratios) = \binom{n}{r} = \frac{n!}{r!(n-r)!} \qquad (4)$$

where *n* is the number of elements (in this case 325) and *r* is number of classes (in this case 2).

Ratios are calculated using Python. Excel table with landmark position is given to the Python script and excel table with all possible ratios is the output. *Distances.py* script calculates distances between landmarks from *fg-net_coordinates.xlsx*.

Distances.py

```
from xlrd import open_workbook
from xlwt import Workbook
import math

wb = open_workbook('fg-net_coordinates.xlsx')
sheet=wb.sheet_by_index(0)
coordinates=[0]*52
distance=0
for row in range(2,sheet.nrows):
        for col in range(3,sheet.ncols):
                coordinates[col-3]=sheet.cell(row,col).value
        print coordinates
        for i in range(0,len(coordinates),2):
                for j in range(0,len(coordinates),2):
                        if j>i:
```

```
					distance=math.sqrt(((coordinates[j]-coordinates[i])*(coordinates[j]-coordinates[i]))+((coordinates[j+1]-coordinates[i+1])*(coordinates[j+1]-coordinates[i+1])))
					logfile=open("distances.csv", "a")
					logfile.write(str(distance) + ";")
					logfile.close()
	logfile=open("distances.csv", "a")
	logfile.write("\n")
	logfile.close()
```

Ratios.py script calculates the ratios from distances given in *distances.xlsx*.

Ratios.py

```
from xlrd import open_workbook
from xlwt import Workbook
import math

wb = open_workbook('distances.xlsx')
sheet=wb.sheet_by_index(1)
distances=[0]*326
ratio=0

for row in range(2,sheet.nrows):
	for col in range(1,sheet.ncols):
		distances[col-1]=float(sheet.cell(row,col).value)
	print distances
	for i in range(0,30):
		for j in range(0,len(distances)):
			if j>i:
				ratio=distances[i]/distances[j]
				logfile=open("ratios.csv", "a")
				logfile.write(str(ratio) + ";")
				logfile.close()
	logfile=open("ratios.csv", "a")
	logfile.write("\n")
	logfile.close()
```

The number of ratios is 52650. It is obvious that this is too large a number to do computations with, so only the important ratios need to be selected. These ratios are defined by using correlation between ratios and age of a person. First, scatter matrices are plotted (Figure 3.10. Correlation between years and ratio d(MFL,LAML)/d(MFL, MFR) and Figure 3.11. Correlation between years and ratio d(MFL,PHR)/d(PHL, LAML)) using IBM SPSS Statistics software. It can be seen that correlation between ratios and age is non-linear.

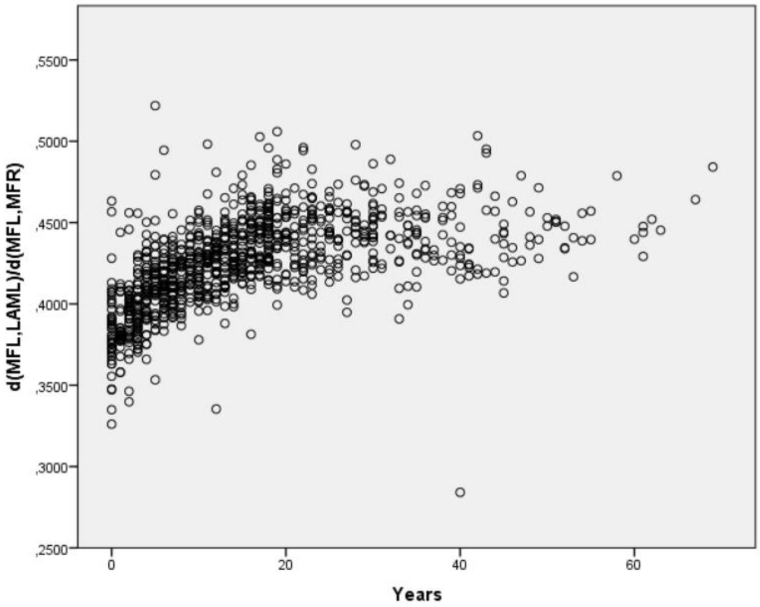

Figure 3.10. Correlation between years and ratio d(MFL,LAML)/d(MFL, MFR)

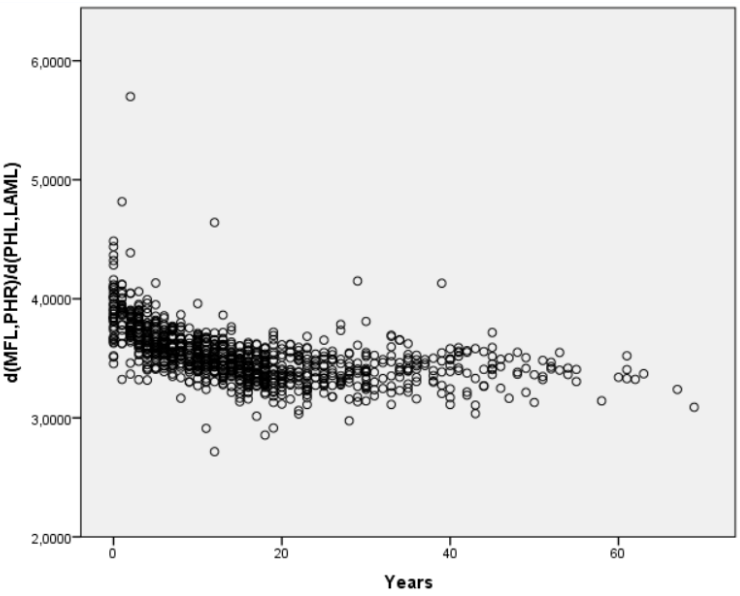

Figure 3.11. Correlation between years and ratio d(MFL,PHR)/d(PHL, LAML)

In order to calculate the correlation between ratios and age, Spearman coefficient is used.

Table 3.3. Spearman coefficients

Ratio	**Spearman coefficient**	**Ratio**	**Spearman coefficient**
d(MFL, LAML)/d(MFL,PHR)	0.653	d(LMLC,LMLEL)/d(LEL,LMLER)	0.614
d(MFL, LAML)/d(MLF,MFR)	0.669	d(LMLC,LMLEL)/d(LEL,MER)	0.609
d(MFL, LAML)/d(PHL,PHR)	0.612	d(LMLC,LMLEL)/d(HEL,LER)	0.653
d(MFL, LAML)/d(PHL,MFR)	0.639	d(LMLC,LMLEL)/d(HEL,HER)	0.628
d(MFL,LMLC)/d(MFL,MFR)	0.627	d(LMLC,LMLEL)/d(HEL,LMLER)	0.620
d(MFL,PHR)/d(LMLC,LMLEL)	0.609	d(LMLC,LMLEL)/d(LMLEL,LER)	0.631
d(MFL,PHR)/d(LAMR,PHR)	0.630	d(LMLC,LMLEL)/d(LMLEL,HER)	0.616
d(MFL,PHR)/d(LAMR,MFR)	0.641	d(LMLC,LMLEL)/d(MEL,LER)	0.666
d(MFL,PHR)/d(PHL,LAML)	0.667	d(LMLC,LMLEL)/d(MEL,HER)	0.629
d(MFL,MFR)/d(LMLC,LMLEL)	0.634	d(LMLC,LMLEL)/d(MEL,LMLER)	0.611
d(MFL,MFR)/d(LMLC,MEL)	0.608	d(LMLC,MEL)/d(LEL,LER)	0.617
d(MFL,MFR)/d(LAMR,PHR)	0.648	d(LMLC,MEL)/d(LEL,HER)	0.608
d(MFL,MFR)/d(LAMR,MFR)	0.667	d(LMLC,MEL)/d(HEL,LER)	0.613
d(MFL,MFR)/d(PHR,MFR)	0.659	d(LMLC,MEL)/d(MEL,LER)	0.629
d(MFL,MFR)/d(PHL,LAML)	0.682	d(LMLC,MEL)/d(MEL,HER)	0.600
d(MFL,MFR)/d(LMLC,PHR)	0.623	d(LMLC,LER)/d(LEL,HER)	0.610
d(MFL,MFR)/d(LMLC,MFR)	0.625	d(LMLC,HER)/d(LEL,HER)	0.610
d(PHL,LAML)/d(PHL,PHR)	0.629	d(LMLC,LMLER)/d(LEL,LER)	0.619
d(PHL,LAML)/d(PHL,MFR)	0.656	d(LMLC,LMLER)/d(LEL,HER)	0.637
d(PHL,PHR)/d(LAMR,MFR)	0.606	d(LMLC,LMLER)/d(LEL,LMLER)	0.620
d(PHL,MFR)/d(LAMR,MFR)	0.641	d(LMLC,LMLER)/d(LEL,MER)	0.627
d(LMLC,LEL)/d(LEL,LER)	0.626	d(LMLC,LMLER)/d(HEL,HER)	0.606
d(LMLC,LEL)/d(LEL,HER)	0.602	d(LMLC,LMLER)/d(LMLEL,HER)	0.601
d(LMLC,LEL)/d(HEL,LER)	0.625	d(LMLC,LMLER)/d(MEL,LER)	0.605
d(LMLC,LEL)/d(LMLEL,LER)	0.601	d(LMLC,LMLER)/d(MEL,HER)	0.618
d(LMLC,LEL)/d(MEL,LER)	0.633	d(LMLC,MER)/d(LEL,LER)	0.614
d(LMLC,HEL)/d(LEL,LER)	0.608	d(LMLC,MER)/d(LEL,HER)	0.623
d(LMLC,HEL)/d(HEL,LER)	0.609	d(LMLC,MER)/d(LEL,LMLER)	0.605
d(LMLC,HEL)/d(MEL,LER)	0.609	d(LMLC,MER)/d(LEL,MER)	0.610
d(LMLC,LMLEL)/d(LEL,LER)	0.646	d(LMLC,MER)/d(MEL,LER)	0.605
d(LMLC,LMLEL)/d(LEL,HER)	0.630	d(LMLC,MER)/d(MEL,HER)	0.606

After calculation of Spearman coefficient, only 62 ratios with high correlation are selected for further calculation. Other ratios have medium or low correlation. The selected ratios and their correlation coefficient can be seen in Table 3.3. Spearman coefficients.

3.2. Classification

Classification in the algorithm is done with neural networks. More precisely, multi layer perceptron is used. Classification is done in IBM SPSS Statistics software.

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the structure of the information processing system. The system is composed of a large number of highly interconnected processing elements (neurones) working in unison to solve specific problems (Neural Networks, 2015).

The most common type of artificial neural network consists of three layers of units (Neural Networks, 2015):

- Input unit represents the raw information that is fed into the network.
- Each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units.
- Output units depend on the activity of the hidden units and the weights between the hidden and output units.

Dependent variable in this research is variable Class. This variable is predicted using 62 covariates (ratios defined in previous chapter). Covariates are rescaled using Standardized method. The distribution mean and standard deviation for each feature need to be calculated. Than the mean is substracted from each covariate and values of each feature are divided by its standard deviation:

$$x' = \frac{x - mean}{s} \qquad (5)$$

Where *x* is a starting covariate value, *x'* is a new covariate value, *mean* is a distribution mean value and *s* is the standard deviation of distribution.

*Multilayer Perceptron Network.
MLP Class (MLEVEL=N) WITH @100178 @2730 @2731 @2754 @30116 @3050 @30117 @3150 @3197 @31116 @31117 @31136 @5054 @54117 @98177 @98193 @98222 @99177 @100177 @100179 @100180 @100193 @100194 @100195 @100208 @100222 @100223 @100224 @101177 @101222 @105177

```
@105178 @105179 @105180 @106177 @106178 @106180 @2753 @2831 @30100 @3196 @31100
@31101 @5053 @53117 @98178 @98208 @99193 @99222 @100209 @101178 @101193 @101223
@103178 @104178 @105194 @105209 @105222 @105223 @106179 @106222 @106223
 /RESCALE COVARIATE=STANDARDIZED
  /PARTITION  TRAINING=7  TESTING=3  HOLDOUT=0
  /ARCHITECTURE   AUTOMATIC=YES (MINUNITS=1 MAXUNITS=50)
  /CRITERIA TRAINING=BATCH OPTIMIZATION=SCALEDCONJUGATE
LAMBDAINITIAL=0.0000005 SIGMAINITIAL=0.00005 INTERVALCENTER=0
INTERVALOFFSET=0.5 MEMSIZE=1000
  /PRINT CPS NETWORKINFO SUMMARY CLASSIFICATION SOLUTION IMPORTANCE
  /PLOT NETWORK ROC GAIN LIFT PREDICTED
  /SAVE PREDVAL
  /STOPPINGRULES ERRORSTEPS= 1 (DATA=AUTO) TRAININGTIMER=ON (MAXTIME=15)
MAXEPOCHS=AUTO ERRORCHANGE=1.0E-4 ERRORRATIO=0.0010
 /MISSING USERMISSING=EXCLUDE .
```

In order to train the neural network, 70% (689) of cases are used. The other 30% (313) are used for testing. The cases were assigned randomly. All the cases were valid and none were excluded (Table 3.4. MLP case processing summary).

Table 3.4. MLP case processing summary

		N	Percent
Sample	Training	689	68,8%
	Testing	313	31,2%
Valid		1002	100,0%
Excluded		0	
Total		1002	

The network has 62 units in the inpute layer. There is only one hidden layer with 8 units. Output layer has 2 units. Activation function for hidden layers is Hyperbolic tangent. This function is defined as the ratio between the hyperbolic sine and the cosine functions or expanded as the ratio of the half-difference and half-sum of two exponential functions in the points x and –x as follows (Karlik and Olgac, 2010):

$$\tanh(x) = \frac{\sinh(x)}{\cosh(x)} = \frac{e^x - e^{-x}}{e^x + e^{-x}} \qquad (6)$$

Activation function for output layer is softmax (Shimodaira, 2015):

$$y_k = \frac{\exp(a_k)}{\sum_l exp a_l}, a_k = \sum_{i=0}^{d} w_{ki}\, x_i \qquad (7)$$

According to Karlik and Olgac (2010) hyperbolic tangent function has better recognition accuracy than other functions. The same results have been obtained in this research (Table 3.5. MLP information).

Table 3.5. MLP information

	Number of Units[a]	62
	Rescaling Method for Covariates	Standardized
Hidden Layer(s)	Number of Hidden Layers	1
	Number of Units in Hidden Layer 1[a]	8
	Activation Function	Hyperbolic tangent
Output Layer	Dependent Variables 1	Manje
	Number of Units	2
	Activation Function	Softmax
	Error Function	Cross-entropy

The results of the trained neural network can be seen in Table 3.6. Trained MLP results.

Table 3.6. Trained MLP results

Sample	Observed	Predicted		
		1	2	Percent Correct
Training	1	373	68	84,6%
	2	53	195	78,6%
	Overall Percent	61,8%	38,2%	82,4%
Testing	1	164	35	82,4%
	2	31	83	72,8%
	Overall Percent	62,3%	37,7%	78,9%

Chapter 4: Experimental Results

This chapter shows the results got after testing the algorithm on various datasets. First part of the chapter describes datasets used, and the second part of the chapter gives performance measurements.

4.1. Datasets

In order to create an accurate algorithm for age classification, appropriate datasets for training and testing are required. There is only one publicly available dataset that can be used for this research (Fg-net) (Lanitis, 2008) and it is described in detail. In order to develop a more accurate algorithm, a private database with facial images is created for algorithm training.

4.1.1. Public Databases

There is a large number of databases available for human age estimation research: Fg-net Aging Database (Fg-net, 2014), MORPH Database (Morph, 2014), YGA Database (Fu and Huang, 2008), WIT-DB Database (Ueki, Hayashida and Kobayashi, 2006), AI&R Asian Face Database (Fu and Zheng, 2006), Burt's Caucasian Face Database (Burt and Perrett, 1995), LHI Face Database (Yao, Yang and Zhu, 2007), HOIP Face Database (Nakano and Fukumi, 2005), Iranian Face Database (Bastanfard, Nik and Deshibi, 2007), Gallagher's Web-Collected Database (Gallagher and Chen, 2008), Ni's Web-Collected Database (Ni, Song and Yan, 2009) and PAL database (Pal database, 2014). An overview of these databases can be seen in Table 4.1. Face age databases.

Some of these databases are not appropriate for this research. YGA, WIT-DB, AI&R, and LHI database are databases of Asian subjects, and population for this research is caucasians. HOIP database has age labels distributed in 10 groups with five year intervals and Gallagher's Web-collected database has age labels in seven categories, which is not accurate enough. Burt's Caucasian Face Database and MORPH database have subjects aged respectively, between 20 and 62 and between 16 and 77, which is not the age range interesting for this research.

The only two databases appropriate for this research are Fg-net database and Ni's web collected database.

Table 4.1. Face age databases

Database name	**No. of subjects**	**No. of images**	**Age**	**Race**	**Labels**
Fg-net	82	1002	0-69	Caucasoid	70 categories
MORPH Public Release	13000	55000	16-77	Caucasoid, Negroid and Mongoloid	62 categories
YGA	1600	8000	0-93	Mongoloid	-
WIT-DB	5500	12008	3-85	Mongoloid	11 categories
AI&R	17	34	22-61	Mongoloid	-
BURT'S	147	147	20-62	Caucasoid	-
LHI	8000	8000	9-89	Mongoloid	-
HOIP	300	306600	15-64	-	10 categories
IRANIAN	616	3600	2-85	Mongoloid	-
GALLAGHER'S	N/A	28231	-	-	7 categories
NI'S	-	219892	1-80	-	-
PAL	575	-	18-93	Caucasoid, Negroid and Mongoloid	-

Only Fg-net database will be used for algorithm testing because the majority of state of the art research use this database (Table 4.2. Face age database by number of papers). Ni's database will not be used for testing because there are no results to compare the algorithm with.

Table 4.2. Face age databases by number of papers

Database	No. of papers
Fg-net	60
MORPH	16
PAL	9
Private databases	17
Other	20

The Fg-net (Face and Gesture Recognition Research Network) ageing database (Fg-net, 2014) is a publicly available ageing database that has been extensively used for evaluation by researchers. The database is composed of 1,002 images of 82 subjects. There are 607 images of male subjects and 395 images of female subjects from 34 female subjects and 48 male subjects (Table 4.3. Subjects and images by sex in Fg-net database) in the age range 0–69 years (Ricanek et al.).

Table 4.3. Subjects and images by sex in Fg-net database

	Number of subjects	Number of images
Female	34	395
Male	48	607
Total	82	1002

The database predominantly includes images in the age range 0–18 years. The images are manually annotated with 68-landmark features and include information on image size, age, gender, presence of facial hair and eyeglasses, horizontal pose, and vertical pose. Many of the images are scanned from photographs and these images exhibit common noise errors associated with old photographs (Ricanek et al.).

Most subjects provided from 10 to 13 images of themselves, 6 subjects provided less than 10 images, and 20 subjects provided more than 13 images (Table 4.4. Images per person in Fg-net database).

Table 4.4. Images per person in Fg-net database

	6	8	9	10	11	12	13	14	15	16	18
Male	1	3	1	7	8	7	11	6	1	3	0
Female	0	0	1	3	7	7	6	3	3	3	1
Total	1	3	2	10	15	14	17	9	4	6	1

Regarding number of images per age, the largest number of images is of age of 18, the smallest number is of age 46 and above. Some ages don't have images associated with them (age 56, 57 59, 64, 65, 66 and 68) (Table 4.5. Images per age in Fg-net database).

Table 4.5. Images per age in Fg-net database

Age	Number of images	Age	Number of images	Age	Number of images	Age	Number of images
0	43	**16**	37	**32**	4	**48**	3
1	27	**17**	28	**33**	9	**49**	3
2	39	**18**	47	**34**	8	**50**	2
3	42	**19**	23	**35**	11	**51**	3
4	42	**20**	20	**36**	8	**52**	3
5	40	**21**	16	**37**	3	**53**	2
6	41	**22**	17	**38**	5	**54**	2
7	41	**23**	22	**39**	6	**55**	2
8	31	**24**	9	**40**	9	**58**	1
9	25	**25**	17	**41**	6	**60**	1
10	40	**26**	11	**42**	5	**61**	3
11	33	**27**	11	**43**	4	**62**	1
12	37	**28**	12	**44**	4	**63**	1
13	32	**29**	9	**45**	7	**67**	1
14	32	**30**	19	**46**	3	**69**	1
15	30	**31**	6	**47**	2		

4.1.2. Private Database

Apart from the databases described in the previous chapter, private database for this research has been created. This database will be used for testing of the algorithm.

Since personal data is collected and used in this research, collection and processing of such data must be in accordance with the Croatian Law on Personal Data Protection. Some of the basic concepts recognized by this Law are (Narodne Novine, 2013):

- Personal information is any information relating to an identified natural person or a natural person who can be identified (respondent); a person who can be identified is the person whose identity can be determined directly or indirectly, in particular on the basis of one or more factors specific to his/her physical, physiological, mental, economic, cultural or social identity.
- Personal data processing is any operation or set of operations which is performed upon personal data, whether or not by automatic means, such as collection, recording, organization, storage, adaptation or alteration, retrieval, consultation, use, disclosure by transmission, dissemination or otherwise made available, alignment or combination, blocking, erasure or destruction, and the implementation of logical, mathematical and other operations on the data.
- Personal data collection is each set of personal data available by specific criteria, whether centralized, decentralized or dispersed on a functional or geographical basis and irrespective of whether it is contained in computer databases or other technical aids or manually.
- Personal data collection director is natural or legal person, public or other body which determines the purposes and means of processing personal data. Once the purpose and method of treatment is prescribed by law, the same law also determines the personal data collection director.
- User is a natural or legal person, public or other body which may use personal data to perform regular activities within its statutory activity.
- Subjects consent is freely given and specific manifestation of the will of the subjects with which he/she expresses consent to the processing of their personal data for specific purposes.

During data collection, respondent was aware of the fact that he/she is giving personal information, aware of the purpose for which the information is collected, and that they can withdraw their data at any time.

Respondent received a Privacy policy for review, which describes the duration of the Privacy policy, all the data collected, the purpose for which the data is collected, and whom to contact in case of any questions. In addition to this policy, all participants signed a statement of consent, with which they give their consent to use their personal data for this research, and confirm that they received for review the Privacy policy mentioned earlier. Since this research collects personal data of minors, their parents/guardians gave consent for the use of these data.

Images were collected during two years. Subjects were asked to provide images of themselves from childhood to adulthood. Every subject had to provide a minimum of 4 images.Images of all subjects have been collect according to Privacy policy described earlier, and all subjects signed the Declaration of conformity with which they stated that their images may be used for this research.

The basic information collected is shown in Table 4.6. Information collected for the private database.

Table 4.6. Information collected for the private database

Field	**Field definition**
ID	Identifier of the subject
IM_ID	Image identifier
IM_AGE	Age of subject in image
DOB	Date of birth
DOA	Date of Acquisition
Gender	Male or female

During data collection, images of 287 subjects have been collected, 151 female and 136 male subjects (Table 4.7. Subjects per sex collected for the private database). In total, 1655 images have been collected.

Table 4.7. Subjects per sex collected for the private database

	Number of subjects
Female	151
Male	136
Total	287

The subjects were asked to provide a minimum of four images. Most of the subjects provided five images, but some of them provided more than eleven (Table 4.8. Images per person collected for the private database). Only six subjects provided a minimum of four images.

Table 4.8. Images per person collected for the private database

	4	**5**	**6**	**7**	**8**	**9**	**10**	**11+**
Male	6	101	9	12	5	2	1	0
Female	0	112	15	11	3	2	7	1
Total	6	213	24	33	8	4	8	1

Regarding number of images per age, the largest number of images is of age of twenty, the smallest number is of age 21 and above. All other age have similar number of images (Table 4.9. Images per age collected for the private database).

Table 4.9. Images per age collected for the private database

Age	**Number of images**	**Age**	**Number of images**	**Age**	**Number of images**
0	21	9	67	18	87
1	81	10	77	19	74
2	131	11	48	20	136
3	78	12	87	21	1
4	56	13	49	22	8
5	73	14	93	23	3
6	84	15	56	24	2
7	99	16	113	25	4
8	55	17	72		

All of the images provided cannot be used for age classification and estimation. Some of the images are of low quality, some have face images from different angles and some have bad lighting. So selection of these images needs to be done. The next step was to crop only faces from the images. After that, images with at least 100 pixels width and height were selected. After this selection 867 images from 242 subjects are left and 788 images have been left out (Table 4.10. Subjects per sex left in the private database after preprocessing).

Table 4.10. Subjects per sex left in the private database after preprocessing

	Number of subjects left
Female	121
Male	121
Total	242

Regarding number of images per age, the largest number of images is still of age of twenty and the smallest number is of age 21 and above (Table 4.11. Images per age left in the private database after preprocessing).

Table 4.11. Images per age left in the private database after preprocessing

Age	Number of images
0	11
1	54
2	51
3	47
4	25
5	47
6	40
7	59
8	31

Age	Number of images
9	43
10	54
11	26
12	28
13	15
14	41
15	43
16	59
17	29

Age	Number of images
18	50
19	43
20	65
21	1
22	3
23	0
24	0
25	2

In order to apply the algorithm to this database, positions of characteristic points need to be determined. The positions are selected manually using a script explained earlier.

4.2. Performance Measurement

The performance is evaluated in two parts. First, the performance evaluation of classification algorithm is done. Next, the performance evaluation of age estimation algorithm is done. Fg-net database and private database are used for testing.

4.2.1. Age Classification

In order to asses the performance of the classifier different measures are used. Confusion matrix will be created and accuracy, precision, recall and specificity will be calculated. Confusion matrix (Kohavi and Provost, 1998) contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix. The confusion matrix shows how algorithm makes predictions. The rows correspond to the actual class of the data. The columns correspond to the predicted values. The value of each of element in the matrix is the number of predictions made with the class corresponding to the column for examples with the correct value as represented by the row (Table 4.12. General confusion matrix (Lecture Notes, 2015)). The diagonal elements show the number of correct classifications made for each class, and the off-diagonal elements show the errors made (Lecture Notes, 2015).

Table 4.12. General confusion matrix (Lecture Notes, 2015)

		Predicted	
		Class 1	**Class 2**
Actual	**Class 1**	TP	FN
	Class 2	FP	TN

True positives (TP) is the number of correct predictions that an instance is positive. True negative (TN) is the number of correct predictions that an instance is negative. False positives (FP) is the number of incorrect predictions that an instance is positive. False negatives (FN) is the number of incorrect predictions that an instance is negative (Lecture Notes, 2015).

Accuracy is the proportion of the total number of predictions that were correct (Lecture Notes, 2015):

$$Accuracy = \frac{TP+TN}{N} * 100\% \qquad (8)$$

It is actually a measure of how often the classifier is correct.

Precision is the proportion of positive cases that were correctly identified:

$$Precision = \frac{TP}{TP+FP} * 100\% \qquad (9)$$

Recall is the proportion of actual positive cases which are correctly identified (Lecture Notes, 2015):

$$Recall = \frac{TP}{TP+FN} * 100\% \qquad (10)$$

Specificity is the proportion of negative cases that were correctly identified (Lecture Notes, 2015):

$$Specificity = \frac{TN}{FP+TN} * 100\% \qquad (11)$$

If the algorithm is applied to samples from Fg-net database, confusion matrix is created based on results of the algorithm (Appendix A) and is as shown in Table 4.13. Confusion matrix for the new algorithm tested on the Fg-net database.

Table 4.13. Confusion matrix for the new algorithm tested on the Fg-net database

		Predicted	
		Child	**Adult**
Actual	**Child**	537	103
	Adult	84	278

The child in this case is defined as a person from age of 0 to age 17. A person from age of 18 and above is defined as an adult.

The value of TP is 537, TN is 278, FP is 84 and FN is 103. Using these values, accuracy, precision, recall and specificity are calculated.

$$Accuracy = \frac{TP + TN}{N} * 100\% = \frac{537 + 278}{1002} * 100\% = 81.34\%$$

$$Precision = \frac{TP}{TP + FP} * 100\% = \frac{537}{537 + 84} * 100\% = 86.47\%$$

$$Recall = \frac{TP}{TP + FN} * 100\% = \frac{537}{537 + 103} * 100\% = 83.91\%$$

$$Specificity = \frac{TN}{FP + TN} * 100\% = \frac{278}{84 + 278} * 100\% = 76.80\%$$

The overall accuracy is **81.34%** which confirms the first hypothesis:

HYPOTHESIS 1

The newly developed algorithm distinguishes children from adults based on facial anthropometric ratios with an accuracy of more than 80% when used on the publicly available Fg-net database.

Table 4.14. Classification accuracy of the new algorithm by age tested on the Fg-net database gives a detailed accuracy for each age. The accuracy decreases when nearing the age 17 which is a threshold for classification. This is logical, because 17 is the threshold age, and closer the age of a person gets to the threshold, the accuracy decreases.

Table 4.14. Classification accuracy of the new algorithm by age tested on the Fg-net database

Age	No. of photos	Correctly classified	Wrongly classified	Accuracy (%)
0	43	43	0	100.00
1	27	26	1	96.30
2	39	38	1	97.44
3	42	42	0	100.00
4	42	36	6	85.71
5	40	39	1	97.50
6	41	40	1	97.56
7	41	38	3	92.68
8	31	29	2	93.55
9	25	20	5	80.00
10	40	36	4	90.00
11	33	28	5	84.85
12	37	30	7	81.08
13	32	22	10	68.75
14	32	23	9	71.88
15	30	19	11	63.33
16	37	15	22	40.54
17	28	13	15	46.43
18	47	36	11	76.60
19	23	17	6	73.91
20	20	13	7	65.00
21	16	13	3	81.25

22	17	11	6	64.71
23	22	16	6	72.73
24	9	8	1	88.89
25	17	13	4	76.47
26	11	8	3	72.73
27	11	8	3	72.73
28	12	11	1	91.67
29	9	9	0	100.00
30	19	14	5	73.68
31	6	5	1	83.33
32	4	3	1	75.00
33	9	5	4	55.56
34	8	6	2	75.00
35	11	10	1	90.91
36	8	6	2	75.00
37	3	2	1	66.67
38	5	5	0	100.00
39	6	4	2	66.67
40	9	7	2	77.78
41	6	4	2	66.67
42	5	3	2	60.00
43	4	3	1	75.00
44	4	4	0	100.00
45	7	5	2	71.43
46	3	1	2	33.33
47	2	1	1	50.00
48	3	2	1	66.67
49	3	3	0	100.00
50	2	2	0	100.00
51	3	3	0	100.00
52	3	3	0	100.00
53	2	1	1	50.00
54	2	2	0	100.00
55	2	2	0	100.00
58	1	1	0	100.00
60	1	1	0	100.00
61	3	3	0	100.00
62	1	1	0	100.00
63	1	1	0	100.00
67	1	1	0	100.00
69	1	1	0	100.00

4.2.2. *Age Estimation*

One of the important aspescts of age estimation problem is finding the best metric for assesing the performance of age estimation algorithm. Two metrics most often used in literature for quantifying the performance of age estimation algorithms are mean absolute error (MAE) and cumulative score (CS) (Geng, Zhou and Smith-Miles, 2007).

The MAE is defined as the average of the absolute errors between the estimated age labels and the cronological age labels (Fu, Guo and Huang, 2010)

$$MAE = \frac{SAE}{N} = \frac{\sum_{i=1}^{N} |x_i - \hat{x}_i|}{N} \qquad (12)$$

where x_i is the cronological age, $\hat{x}_i$ is the estimated age, *SAE* is the sum of the absolute errors and *N* is the number of test images (Hamilton, 1994).

MAE has two other variations: MAE per age and MAE per decade. Both of these variations will be used in this research. MAE per age measures the mean absolute error at each age, and MAE per decade computes mean absolute error for every ten years (Guo, 2012).

The CS metric is defined as the proportion of test images such that the absolute error is not higher than an integer j:

$$CS(j) = \frac{N_{e \leq j}}{N_x} * 100\% \qquad (13)$$

where $N_{e \leq j}$ is the number of test images on which the absolute error in age estimation is within *j* years (Turaga, Biswas and Chellapa, 2010), (Chen et al., 2011).

New algorithm tested on Fg-net database

When algorithm is used on Fg-net database the general MAE is 6.67. Other than general MAE measure, MAE per age and MAE per decade are also important measures. Table 4.15. MAE per age results of the new algorithm tested on the Fg-net database gives an overview of MAE per age. The results of MAE per age measure are consistent with theories given in literature that say that anthropometric ratios are more accurate for younger ages. All the algorithm results for Fg-net database can be seen in Appendix A.

Table 4.15. MAE per age results of the new algorithm tested on the Fg-net database

Age	No.of images	MAE per age	Age	No.of images	MAE per age
0	43	3.81	32	4	10.00
1	27	3.11	33	9	12.89
2	39	3.82	34	8	14.63
3	42	3.62	35	11	12.00
4	42	6.05	36	8	13.25
5	40	4.95	37	3	18.33
6	41	4.37	38	5	14.80
7	41	4.46	39	6	18.33
8	31	4.52	40	9	17.44
9	25	4.72	41	6	22.00
10	40	4.75	42	5	18.00
11	33	4.94	43	4	17.50
12	37	5.30	44	4	19.75
13	32	5.31	45	7	25.29
14	32	5.31	46	3	24.67
15	30	4.90	47	2	20.00
16	37	5.89	48	3	26.33
17	28	4.43	49	3	25.67
18	47	4.91	50	2	27.50
19	23	5.57	51	3	26.00
20	20	4.15	52	3	27.67
21	16	3.56	53	2	30.00
22	17	5.41	54	2	32.50
23	22	4.64	55	2	29.00
24	9	3.00	58	1	29.00
25	17	3.94	60	1	39.00
26	11	5.00	61	3	34.00
27	11	6.91	62	1	40.00
28	12	5.33	63	1	36.00
29	9	6.56	67	1	38.00
30	19	8.95	69	1	36.00
31	6	5.67			

An overview of MAE per decade is given in Table 4.16. MAE per decade results of the new algorithm tested on the Fg-net database. The acceptable MAE per decade is for first three decades, whereas the MAE per decade for ages 30 and above is too large.

Table 4.16. MAE per decade results of the new algorithm tested on the Fg-net database

Age range	No. of images	MAE per decade
0-9	371	4.37
10-19	339	5.12
20-29	144	4.74
30-39	79	12.08
40-49	46	21.20
50-59	15	28.53
60-69	8	36.38

The other measure used in most of the literature on age estimation is cumulative score.

Cumulative score for error levels of 0 to 20 is shown in Table 4.17. CS results of the new algorithm tested on the Fg-net database and Figure 4.10. Cumulative score curve of the new algorithm tested on the Fg-net database

Table 4.17. CS results of the new algorithm tested on the Fg-net database

Error level	No. of samples	Cumulative score (CS)	Error level	No. of samples	Cumulative score (CS)
0	66	6.59	11	26	
1	116	18.16	12	18	
2	115		13	16	
3	104		14	15	
4	90		15	12	90.12
5	91	58.08	16	11	
6	68		17	10	
7	50		18	7	
8	41		19	9	
9	36		20	4	94.21
10	39	81.44			

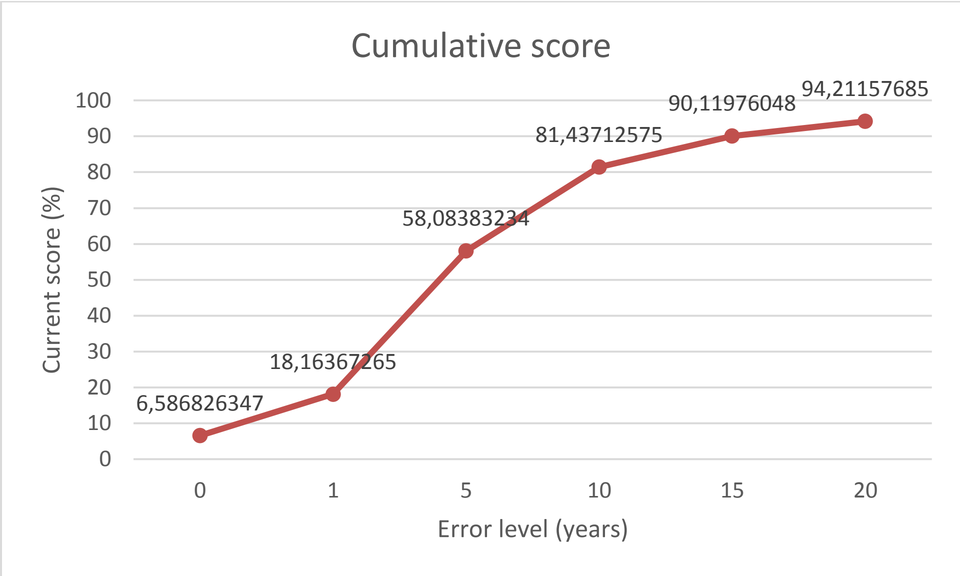

Figure 4.10. Cumulative score curve of the new algorithm tested on the Fg-net database

These results will be compared with the results of age estimation using an anthropometric model on Fg-netdatabase.

Anthropometric model tested on Fg-net database

In order to compare the existing algorithm with the anthropometric model, the anthropometric model has to be evaluated on the Fg-net database.

The six ratios used in anthropometric model are different ratios than those used in the new algorithm (Table 4.18. Face ratios used in anthropometric model).

Table 4.18. Face ratios used in anthropometric model

Ratio name	**Ratio formula**
Ratio 1	LEYE-REYE/EYE-NOSE
Ratio 2	LEYE-REYE/EYE-LIP
Ratio 3	EYE-NOSE/EYE-CHIN
Ratio 4	EYE-NOSE/EYE-LIP
Ratio 5	LEYE-REYE/EYE-CHIN
Ratio 6	THEAD-CHIN/EYE-CHIN

The general MAE for anthropometric model is **7.03**. Compared with MAE for the new algorithm where MAE is **6.67**, it can be seen that ratios in the new algorithm give better results. All the anthropometric model results for Fg-net database can be seen in Appendix B.

Table 4.19. Comparison of MAE per age results of the new algorithm and anthropometric model tested on the Fg-net database shows the values of MAE per age of anthropometric model (AM) in comparison to MAE per age of the new algorithm. In most cases, MAE per age of the new algorithm is better than MAE per age of AM. The cases where MAE per age of AM is better than MAE per age of the new algorithm are for age of 45 and above, where the number of samples is small.

Table 4.19. Comparison of MAE per age results of the new algorithm and anthropometric model tested on the Fg-net database

Age	**No.of images**	**MAE new algorithm**	**MAE AM**
0	43	3.81	4.02
1	27	3.11	5.44
2	39	3.82	6.92
3	42	3.62	6.48
4	42	6.05	10.48
5	40	4.95	10.03
6	41	4.37	10.02
7	41	4.46	12.56
8	31	4.52	11.00
9	25	4.72	14.60
10	40	4.75	16.00
11	33	4.94	16.09
12	37	5.30	16.16
13	32	5.31	17.06
14	32	5.31	18.78
15	30	4.90	19.30
16	37	5.89	20.00
17	28	4.43	19.50
18	47	4.91	19.98
19	23	5.57	20.87
20	20	4.15	20.55

Age	**No.of images**	**MAE new algorithm**	**MAE AM**
32	4	10.00	19.00
33	9	12.89	19.22
34	8	14.63	20.25
35	11	12.00	24.82
36	8	13.25	24.13
37	3	18.33	20.67
38	5	14.80	23.60
39	6	18.33	21.50
40	9	17.44	25.78
41	6	22.00	23.00
42	5	18.00	22.40
43	4	17.50	23.75
44	4	19.75	21.75
45	7	25.29	22.14
46	3	24.67	21.00
47	2	20.00	19.50
48	3	26.33	22.00
49	3	25.67	24.67
50	2	27.50	19.50
51	3	26.00	27.00
52	3	27.67	22.00

21	16	3.56	20.81	53	2	30.00	22.50
22	17	5.41	19.47	54	2	32.50	15.00
23	22	4.64	22.50	55	2	29.00	25.50
24	9	3.00	22.33	58	1	29.00	29.00
25	17	3.94	22.41	60	1	39.00	39.00
26	11	5.00	22.00	61	3	34.00	23.67
27	11	6.91	20.45	62	1	40.00	40.00
28	12	5.33	20.67	63	1	36.00	36.00
29	9	6.56	26.33	67	1	38.00	38.00
30	19	8.95	22.53	69	1	36.00	36.00
31	6	5.67	24.67				

In MAE per decade table, the MAE per decade of anthropometric model is better in cases where there is a small number of samples (Table 4.20. Comparison of MAE per decade results of the new algorithm and anthropometric model tested on the Fg-net database).

Table 4.20. Comparison of MAE per decade results of the new algorithm and anthropometric model tested on the Fg-net database

Age range	**No. of images**	**MAE new algorithm**	**MAE AM**
0-9	371	4.37	8.99
10-19	339	5.12	18.29
20-29	144	4.74	21.56
30-39	79	12.08	22.30
40-49	46	21.20	23.07
50-59	15	28.53	22.47
60-69	8	36.38	25.38

If the cumulative score measure for both algorithms is compared, the cumulative score of the new algorithm is better on every error level. Most importantly, cumulative score for error level 0 is **6.59** for the new algorithm and **0** for anthropometric model. This means that anthropometric model predicts the correct age in 0 cases and the new algorithm predicts the correct age in 66 cases. The comparison of cumulative score curves can be seen in Figure 4.11. Comparison of cumulative score curves of the new algorithm and anthropometric model tested on the Fg-net database.

Table 4.21. Comparison of CS results of the new algorithm and anthropometric model tested on the Fg-net database

Error level	No. of samples New algorithm	Cumulative score (CS) new algorithm	No. of samples AM	Cumulative score (CS) AM
0	66	6.59	0	0.00
1	182	18.16	1	0.10
5	582	58.08	155	15.47
10	816	81.44	289	28.84
15	903	90.12	439	43.81
20	944	94.21	653	65.17

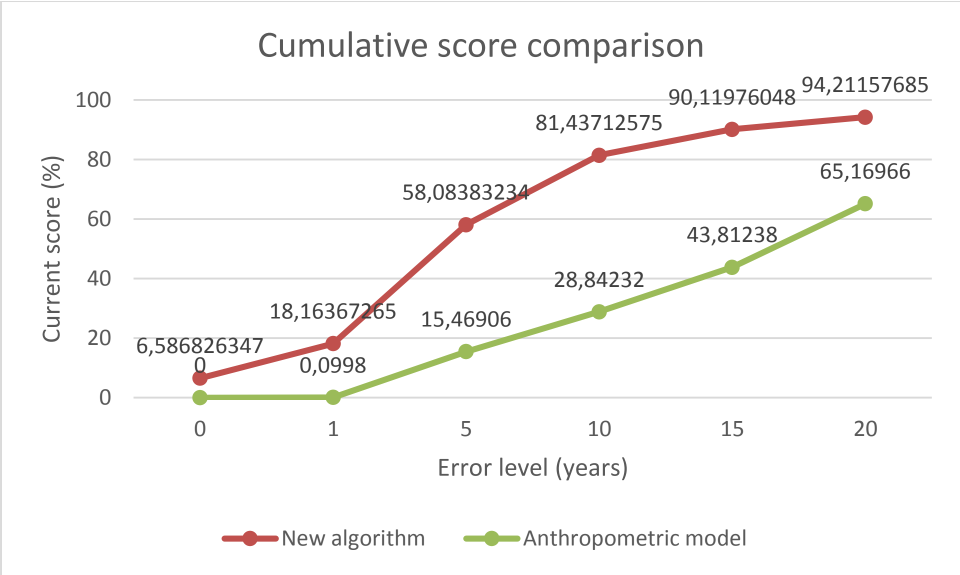

Figure 4.11. Comparison of cumulative score curves of the new algorithm and anthropometric model tested on the Fg-net database

These results confirm the second hypothesis:

HYPOTHESIS 2

Usage of different facial anthropometric ratios than those used in existing anthropometric model, increases the accuracy of the algorithm when used for age estimation.

Private database

As addition to this research, a private database of images is created. If the new algorithm is applied on this database, MAE is 3.25. All the algorithm results for private database can be seen in Appendix C.

MAE per age and MAE per decade values can be seen in Table 4.22. MAE per age results of the new algorithm tested on the private database and Table 4.23. MAE per decade results of the new algorithm tested on the private database. The results are similar to results where algorithm was tested on Fg-net database.

Table 4.22. MAE per age results of the new algorithm tested on the private database

Age	**No.of images**	**MAE**
0	11	3.55
1	54	2.33
2	51	2.12
3	47	3.13
4	25	3.08
5	47	4.19
6	40	3.53
7	59	3.71
8	31	3.52
9	43	2.37
10	54	3.07
11	26	3.12
12	28	2.52

Age	**No.of images**	**MAE**
13	15	2.00
14	41	2.10
15	43	2.35
16	59	2.36
17	29	2.86
18	50	3.94
19	43	4.84
20	65	5.25
21	1	7.00
22	3	7.00
23	0	-
24	0	-
25	2	9.50

Table 4.23. MAE per decade results of the new algorithm tested on the private database

Age range	**No. of images**	**MAE**
0-9	408	3.10
10-19	388	2.99
20-29	71	5.46

The cumulative score values are listed in Table 4.24. CS results of the new algorithm tested on the private database. These values are better than values got when algorithm was tested on the Fg-net database. The reason for that is that the private database was preprocessed, and all images from different angles and with bad resolution were excluded from the database. Also, the private databse has images from age 0 to 25 which makes estimation and classification easier. The resulting curve can be seen in Figure 4.12. Cumulative score curve of the new algorithm tested on the private database.

Table 4.24. CS results of the new algorithm tested on the private database

Error level	No. of samples	Cumulative score (CS)
0	93	10.73
1	262	30.22
5	700	80.74
10	859	99.08
15	867	100.00
20	867	100.00

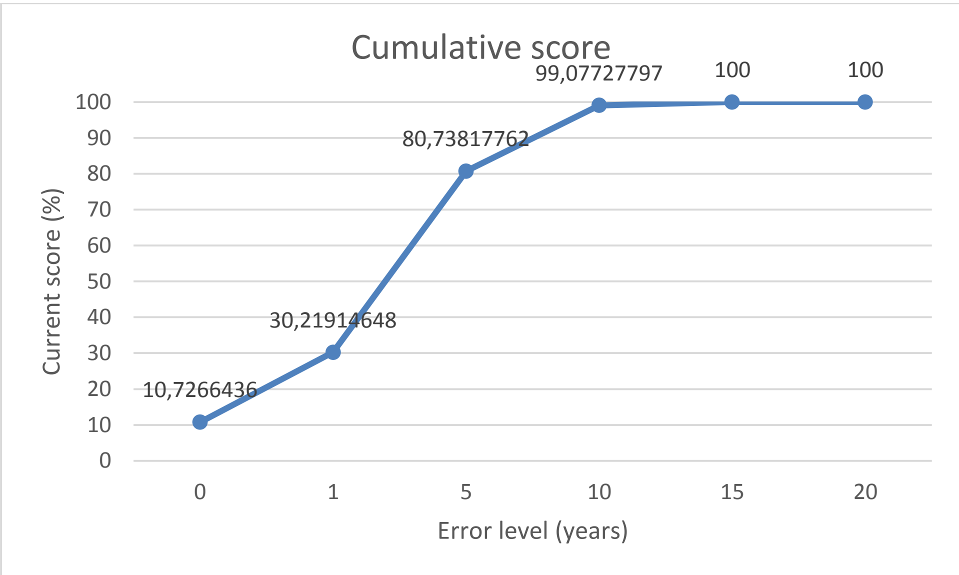

Figure 4.12. Cumulative score curve of the new algorithm tested on the private database

4.3. Comparison with State of the Art Algorithms

In order to position this algorithm in state of the art research, comparison with existing age classification and age estimation algorithms is done. Table 4.25. Current research results for age classification shows the current research results for age classification.

Table 4.25. Current research results for age classification

Algorithm	Database used	Classes	Accuracy
Mohan, Kumar and Krishna (2010)	Part of Fg-netand 500 face images from Google images	16-25, 26-35, 36-45, 46-55, 56-65, 66-75, 76-85	Fg-net– 94.1% Google images – 90.8%
Kwon and Lobo (1999)	47 images	Babies, young adults and senior adults	Not reported
Horng, Lee and Chen (2001)	230 images	0-2, 3-39, 40-59, 60+	81.58%
Nithyashri and Kulanthaivel (2012)	Fg-net	0-12, 13-18, 19-59, 60+	94.28%
Zhou, Miller and Zhang (2011)	Fg-net MORPH	Youths and adults	76% 86%
Zhan, Li and Ogunbona (2011)	Fg-net MORPH	4 groups (0-19, 20-29, 30-39, 40-69) 2 groups (0-10, 11+) 2 groups (0-14, 15+) 2 groups (0-18, 19+) 2 groups (0-20, 21+) 2 groups (0-30, 31+)	60.9% 87.1% 85.9% 85.3% 84.0% 86.3%
Qi and Zhang (2009)	7443 images	Kids and adults	90.46%
Hajizadeh and Ebrahimnezhad (2011)	Iranian Face Database	0-15, 16-30, 31-50, 50+	87.03%
Li et al. (2012)	5080 images from	0-2, 3-7, 8-12, 13-	48.5%

	Flickr	19, 20-36, 37-65, 66+	
Kalamani and Balasubramanie (2006)	250 images	0-2, 3-12, 13-24, 25-40, 41-55, 56+	95%
Shen and Ji (2008)	179 images	Baby and adult	49.72%
Ramesha, Raja and Patnaik (2010)	58 images	0-30, 30-40, 40+	89.65%
Gunay and Nabiyev (2008)	FERET +350 images	10+-5, 20+-5, 30+-5, 40+-5, 50+-5, 60+-5	80%

As it can be seen from Table 4.25. Current research results for age classification, none of the algorithms divide samples in children (age 0 to 17) and adults (age 18 and above). The most similar algorithms that divide samples in two classes and have testing results on Fg-net database are listed in Table 4.26. Research results for age classification comparable to this research. The most accurate algorithm is by Zhan and Ogunbona (2011) where the closest class definition is for class 1 (age 0 to 18) and class 2 (age 19 and above). The accuracy of that algorithm is 85.30%. If the algorithm from this research is tested on the same classes, its accuracy is 79.90%. But if the algorithm from this research is tested on the four classes defined in algorithm by Zhan and Ogunbona, the algorithm from this research has an accuracy of 71.80%, as opposed to Zhan and Ogunbone algorithm accuracy which is 60.90%.

Table 4.26. Research results for age classification comparable to this research

Algorithm	**Database used**	**Classes**	**Accuracy**
Zhou, Miller and Zhang (2011)	Fg-net	Youths and adults	76%
Zhan, Li and Ogunbona (2011)	Fg-net MORPH	4 groups (0-19, 20-29, 30-39, 40-69)	60.9%
		2 groups (0-10, 11+)	87.1%
		2 groups (0-14, 15+)	85.9%
		2 groups (0-18, 19+)	85.3%
		2 groups (0-20,	84.0%

		21+) 2 groups (0-30, 31+)	86.3%

If the algorithm is tested for age estimation, the result is MAE of 6.67, and CS(0) of 6.59%, CS(1) of 18.16%, CS(5) of 58.08383234%, CS(10) of 81.44%, CS(15) of 90.12% and CS(20) of 94.21%.

The MAE and CS results of the state of the art algorithms can be seen in Table 4.27. Current research results for age estimation.

Table 4.27. Current research results for age estimation

Algorithm	Abbreviation	MAE	CS (1)	CS (5)	CS (10)
El Dib and Saban (2010)	EBIF	3.17	58	82	90
Lian et al. (2011)	MTGLOH	3.44	20	78	97
Chao, Liu and Ding (2013)	LSL-AOR	4.11	-	-	-
Luu et al. (2011)	CAM	4.12	23	74	90
Weng et al. (2012)	MFOR	4.25	36	75	88
Li, Wang and Zhang (2012)	Weighte OHRanked	4.32	30	74	90
Luu et al. (2009)	HIE	4.33	-	-	-
Kohli, Prakash and Gupta (2011)	ECDC	4.35	-	-	-
Gao (2012)	CMTSVR	4.37	34	76	90
Chang, Chen and Hung (2011)	OHRank	4.48	38	74	88
Li et al. (2012)	LDMR	4.51	-	-	-
Hu et al. (2013)	LAGF	4.54	41	75	88
Choi et al. (2011)	HC	4.66	33	73	87
Chen et al. (2013)	CA	4.67	-	75	-
Duong et al. (2011)	GLFF	4.74	-	-	-
Yin and Geng (2012)	CPNN	4.76	33	75	88
Guo et al. (2009)	BIF	4.77	20	68	90
Li et al. (2012)	PLO	4.82	33	72	92
Zhang and Yeung (2010)	MTWGP	4.83	10	34	54
Qin et al. (2007)	MHR	4.87	30	64	82
Xiao et al. (2009)	mKNN	4.93	25	75	85
Zhang and Yeung (2010)	WGP	4.95	31	72	88
Guo et al. (2008)	PFA	4.97	28	75	88

Luo et al. (2011)	ML-SVM+BIF	5.04	-	-	-
Kilinc and Akgul (2013)	OAG	5.05	-	-	-
Guo et al. (2008)	LARR	5.07	26	68	88
Long (2009)	Metric Learning + GPR	5.08	20	67	87
Ylioinas et al. (2013)	LBPKDE	5.09	-	-	
Zhang (2012)	TP	5.23	28	68	88
Chang, Chen and Hung (2010)	RED-SVM	5.24	26	60	78
Yan et al. (2007)	BM	5.33	18	64	85
Yan et al. (2007)	RUN2	5.33	19	65	88
Geng and Smith-Miles (2009)	MSA	5.36	-	-	-
Luo et al. (2011)	ML-SVM+LGBP	5.37	-	-	-
Zhang and Yeung (2010)	GP	5.39	26	64	88
Selvi and Vani (2011)	MPCA	5.41	-	-	-
Kou, Du and Zhai (2012)	Global+Local	5.72	-	-	-
Luo et al. (2011)	ML-SVM+PCA	5.73	-	-	-
Lu and Tan (2012)	FSTI	5.75	14	58	84
Yan et al. (2007)	RUN1	5.78	26	68	86
Guo et al. (2008)	SVR	5.91	22	69	89
Suo et al. (2008)	AO graph	5.97	-	-	-
Geng, Zhou and Smith-Miles (2007)	KAGES	6.18	28	63	80
Gunay and Nabiyev (2013)	Radon	6.18	-	-	-
Lanitis, Draganova and Christodoulou (2004)	QM	6.55	13	49	76
Luu et al. (2011)	AAM	6.77	-	-	-
Geng, Zhou and Smith-Miles (2007)	AGES	6.77	26	64	84
Ju and Wang (2009)	LFR	6.85	-	-	-
Lanitis, Draganova and Christodoulou (2004)	MLP	6.98	9	32	59
Dahlan, Mashohor, and Mumtazah (2013)	SGF	7.15	-	-	-
Guo et al. (2008)	SVM	7.25	28	62	78

Zhai, Qing and Ji-Xiang (2010)	INMF	7.26	12	53	78
Lanitis, Taylor and (1999)	WAS	8.06	10	40	78
Geng, Zhou and Zhang (2006)	HumanA	8.13	-	-	-
Ju and Wang (2009)	C4.5	9.34	18	48	68
Ju and Wang (2009)	BP	11.85	12	34	56
Lanitis, Draganova and Christodoulou (2004)	AAS	14.83	8	35	52

If the algorithms are compared by MAE, there are many algorithm that yield better results than the algorithm from this research (Table 4.28. Comparison of state of the art research results for age estimation with the new algorithm results), but the difference is that they all take into consideration not only facial anthropometry, but also wrinkles and skin changes, all of which can be changed with a little makeup or corrective surgery.

Table 4.28. Comparison of state of the art research results for age estimation with the new algorithm results

Abbreviation	**MAE**
EBIF	3.17
MTGLOH	3.44
LSL-AOR	4.11
CAM	4.12
MFOR	4.25
Weighte OHRanked	4.32
HIE	4.33
ECDC	4.35
CMTSVR	4.37
OHRank	4.48
LDMR	4.51
LAGF	4.54
HC	4.66
CA	4.67
GLFF	4.74
CPNN	4.76
BIF	4.77
PLO	4.82

Abbreviation	**MAE**
RED-SVM	5.24
BM	5.33
RUN2	5.33
MSA	5.36
ML-SVM+LGBP	5.37
GP	5.39
MPCA	5.41
Global+Local	5.72
ML-SVM+PCA	5.73
FSTI	5.75
RUN1	5.78
SVR	5.91
AO graph	5.97
KAGES	6.18
Radon	6.18
QM	6.55
New algorithm	6.67
AAM	6.77

MTWGP	4.83	AGES	6.77
MHR	4.87	LFR	6.85
mKNN	4.93	MLP	6.98
WGP	4.95	SGF	7.15
PFA	4.97	SVM	7.25
ML-SVM+BIF	5.04	INMF	7.26
OAG	5.05	WAS	8.06
LARR	5.07	HumanA	8.13
Metric Learning + GPR	5.08	C4.5	9.34
LBPKDE	5.09	BP	11.85
TP	5.23	AAS	14.83

According to cumulative score values, the new algorithm falls somewhere in the middle of state of the art algorithms. The results of state of the art algorithms have been taken from published papers and have not been verified. In some of the algorithms, all images from Fg-net database haven't been used, so this increases their accuracy. The quality of some images from Fg-net database is not appropriate for computer vision, biometric recognition and age estimation (Figure 4.4. Example of image from Fg-net database not appropriate for age estimation).

Figure 4.4. Example of images from Fg-net database not appropriate for age estimation

Chapter 5: Application

Application of age estimation can be divided into several groups. Fu, Guo and Huang (2010) distinguish between applications of age estimation in: forensic art, electronic customer relationship management (eCRM), security control and surveillance monitoring, biometrics, entertainment and cosmetology.

In forensic art, age estimation is used mostly as age progression for suspects, victims and lost person identification (Mancusi). Age progression can predict a person's appearance accross age and thus help in finding missing individuals (Ramanathan, Chellapa and Biswas, 2009). Another problem, described by Schmeling et al. (2006), is the problem of age estimation of unaccompanied minors. The problem arises when foreigners entering the country have no documents for their date of birth. They often make false statements about their age as to avoid being criminaly prosecuted. Current practice is to physicaly examine imigrants, radiographic examination of the hand, radiographic examination of the clavicles and dental examination (Schmeling, 2006). Physical examination includes anthropometric measures such as height, weight, type of constitution and visible signs of sexual maturity. All of the above mentioned measures and practices are intrusive and require experts. One other solution for the problem of unaccompanied minors is the use of computer algorithm that will determine their age based on photographs of their face. There is also a growing problem of pedopornography. With Internet expansion, the problem of child pornography has increased and experts need to evaluate images of victims (Cattaneo et al., 2009). Age estimation can be used to determine the age of victims in images.

Reponen and Tapio (2003) give the definition of eCRM: „The eCRM or electronic customer relationship management encompasses all the CRM functions with the use of the net environment i.e., intranet, extranet and internet. Electronic CRM concerns all forms of managing relationships with customers making use of information technology (IT). ECRM is enterprises using IT to integrate internal organization resources and external "marketing" strategies to understand and fulfill their customers’ needs. Comparing with traditional CRM, the integrated informatioyn for eCRM intraorganizational collaboration can be more efficient for communication with customers. Age estimation in eCRM is used as a part of gathering information about customers to establish customer relations. Different age groups have different needs and preferences and that is where age estimation can be used (Fu, Guo and Huang, 2010).

The most widely spread usage of age estimation is in security control and surveillance monitoring. It can stop minors from entering bars and to prevent underage drinking. It can also prevent minors from buying toobacco products from vending machines. Age estimation can also prevent older people from entering some rides in amusement parks. Another very important thing is using age estimation for denying minors access to web sites for adults (Guo et al., 2008), (Lanitis, Draganova and Christodoulou, 2004), (Ramanathan, Chellapa and Biswas, 2009). Secure internet access control is closely related with human computer interaction. Age estimation can be used to determine the age of users to adjust the type of interaction to their age (Lanitis, Draganova and Christodoulou, 2004). Game levels could be adjusted according to user's age.

In biometrics, age estimation is used as a soft biometric characteristic to improve the performance of biometric systems. It can improve robustness of face recognition systems to time gap (Wang et al., 2006), (Lanitis, 2009) and the task of periodically updating large face databases with recent images could be skipped (Ramanathan, Chellapa and Biswas, 2009), (Lanitis, Draganova and Christodoulou, 2004), (Patterson et al., 2007).

Entertainment and cosmetology are other areas where age estimation is used. Very common effects in movies are aging and rejuvenating of actors, where age estimation and progression are utilized (Blanz and Vetter, 1999). Another usage of age estimation is in age-based retrieval of face images from different databases that can be used for creating e-photoalbums by age-range (Lanitis, Draganova and Christodoulou, 2004).

People have the tendency to want to look younger. Important thing in looking younger is rejuvenating of the face. Age estimation helps to predict the rejuvenating results (Fu et al., 2004).

Chapter 6: Conclusion

Human age classification and estimation from facial images is a growing field of research. Face images contain various information and this research uses two-dimensional face images to classify images to those from children (age 0 to 17) or adults (age 18 and above). Other than this, the research uses face images to estimate the age of a person.

The main objective of this research was to develop an algorithm for human age classification and estimation which can classify humans into children and adults. This new algorithm is based on the model proposed in this research. More specific objectives identified to achieve the main objective are to identify changes on the face that occur during growth and aging, to identify facial landmarks necessary for algorithm creation, to identify ratios needed to create a new age classification and estimation algorithm and to compare the new algorithm accuracy with the accuracy of existing algorithms.

This research gives answers to the three research questions defined at the beginning of this research.

What changes occur on human face during growth and aging?

Analysis of the state of the art research on facial changes during growth and aging gives an answer to this question. To this end, scientific methods of description, compilation, analysis, synthesis, generalization and specialization are used. The answer to this research question is given in Table 2.4. Face shape changes caused by growth or aging in Chapter 2.1. Aging Face.

Which facial landmarks are important for age classification and estimation?

In Chapter 3.1.1. Facial Landmarks, analysis of state of the art research on facial landmarks used for age classification and estimation is given. First, all of the state of the art algorithms are analysed and an overview of landmarks used in those algorithms is given. After that, landmarks that appear at least twice are selected. Selected landmarks are combined with changes that happen on human face during growth and aging, and a set of 26 landmarks used in this research is identified. These landmarks can be seen in Table 3.2. Landmark points used in this research.

Which facial ratios are important for age classification and estimation?

The answer to the last research question identified is given in Chapter 3.1.2. Ratios. First, all Euclidean distances between 26 facial landmarks identified are calculated. There are 325 possible distances. After that, all ratios between those distances are calculated. The number of possible ratios is 52650. This is too large a number to do classification with, so the number needs to be reduced. The correlation between every ratio and age is nonlinear, so Spearman coefficient is calculated. Only ratios that have high correlation coefficient are used for age classification and estimation. This leaves 62 ratios. The answer to this research question is given in Table 3.3. Spearman coefficients.

Other than research questions there are two hypothesis that need to be confirmed.

The newly developed algorithm distinguishes children from adults based on facial anthropometric ratios with an accuracy of more than 80% when used on the publicly available Fg-net database.

The newly developed algorithm uses Multi Layer Perceptron for classification. The 62 ratios identified as an answer to the third research question are used as a basis for the algorithm. Algorithm performance measurements used to test the classification part of the algorithm are explained in Chapter 4.2.1. Age Classification. The accuracy of the algorithm is 81.38% which confirms the first hypothesis. The table with complete results can be seen in Appendix A.

Usage of different facial anthropometric ratios than those used in existing anthropometric model, increases the accuracy of the algorithm when used for age estimation.

In order to compare the results of the ratios from the new algorithm with the results of anthropometric model ratios for age estimation, the anthropometric model needs to be tested on the same database (Fg-net). The MAE value of the new algorithm tested on the Fg-net database is 6.67. The MAE value of the anthropometric model tested on the Fg-net database is 7.03. CS values of the new algorithm for error levels 0, 1, 5, 10, 15 and 20 are as follows: CS(0)=6.59%, CS(1)=18.16%, CS(5)=58.08%, CS(10)=81.44%, CS(15)=90.12% and CS(20)=94.21%. CS values of the anthropometric model for error levels 0, 1, 5, 10, 15 and 20 are as follows: CS(0)=0%, CS(1)=0.10%, CS(5)=15.47%, CS(10)= 28.84%, CS(15)= 43.81% and CS(20)= 65.17%. These values confirm the second hypothesis. The table with complete results can be seen in Appendix B.

The scientific contribution of this research has been explained in Introduction and can be seen in systematization of knowledge on age classification and estimation, identification of facial landmarks relevant for age classification and estimation, using data mining to identify ratios important for age classification and estimation, creation of a new algorithm for age classification and evaluation of anthropometric model on a large database.

Other than scientific, this research has a social contribution also: determining the age of immigrants or asylum seekers in situations where there are no documents proving the age of the person, for websites where entrance is allowed only for persons older than age of 18, in order to improve the system for face recognition (most of them are sensitive to changes during aging), searching for missing persons over the years, in human-computer interaction based on age, for the purpose of predicting a persons aging, in the fight against pedophilia (removing images of minors from various portals or personal computers), etc. The possible application of this research is described in detail in Chapter 5 Application.

Future work will concentrate on improving the algorithm for both classification and estimation. The facial landmarks in this research have been marked manualy. Future research will deal with automatic landmark detection and incorporating it in this algorithm. The private database will be extended and algorithm training will be done on a larger sample. Other than that, application of the algorithm will be further researched and algorithm will be modified to adhere to different fields of application.

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APPENDIX A New algorithm results for Fg-net database

Image ID	Real Age	Real Class	Estimated Class	Estimated Age
13_0	0	1	1	1
15_0	0	1	1	0
19_0	0	1	1	5
22_0	0	1	1	3
23_0	0	1	1	5
24_0	0	1	1	7
25_0	0	1	1	2
26_0	0	1	1	1
30_0	0	1	1	8
31_0	0	1	1	4
35_0	0	1	1	8
36_0	0	1	1	0
37_0	0	1	1	2
38_0	0	1	1	0
40_0	0	1	1	9
41_0	0	1	1	4
42_0	0	1	1	0
43_0	0	1	1	0
46_0	0	1	1	0
48_0	0	1	1	1
50_0	0	1	1	0

Image ID	Real Age	Real Class	Estimated Class	Estimated Age
66_8	8	1	1	14
70_8	8	1	1	3
73_8	8	1	1	13
74_8	8	1	1	6
75_8	8	1	1	3
76_8	8	1	1	7
77_8	8	1	1	7
78_8	8	1	2	22
79_8	8	1	1	13
8_8	8	1	1	11
80_8	8	1	1	18
81_8	8	1	1	9
10_9	9	1	2	17
15_9	9	1	1	16
23_9	9	1	1	8
31_9	9	1	2	23
35_9	9	1	1	10
37_9	9	1	1	10
40_9	9	1	1	19
41_9	9	1	1	16
47_9	9	1	1	14

Image ID	Real Age	Real Class	Estimated Class	Estimated Age
45_18	18	2	2	24
46_18	18	2	2	21
47_18	18	2	2	21
48_18	18	2	2	21
5_18	18	2	2	19
50_18	18	2	2	29
51_18	18	2	2	26
52_18	18	2	2	19
53_18	18	2	2	25
54_18	18	2	2	26
57_18	18	2	2	23
61_18	18	2	2	26
62_18	18	2	2	23
63_18	18	2	2	28
7_18	18	2	2	24
71_18	18	2	1	13
8_18	18	2	2	24
82_18	18	2	2	27
9_18	18	2	1	16
1_19	19	2	2	29
13_19	19	2	1	16

51_0	0	1	1	4
53_0	0	1	1	15
54_0	0	1	1	13
57_0	0	1	1	3
58_0	0	1	1	13
63_0	0	1	1	2
66_0	0	1	1	4
68_0	0	1	1	6
69_0	0	1	1	1
70_0	0	1	1	0
71_0	0	1	1	2
73_0	0	1	1	11
74_0	0	1	1	0
75_0	0	1	1	4
76_0	0	1	1	1
77_0	0	1	1	0
78_0	0	1	1	9
79_0	0	1	1	2
80_0	0	1	1	5
81_0	0	1	1	3
82_0	0	1	1	1
9_0	0	1	1	5
10_1	1	1	1	1
15_1	1	1	1	0
16_1	1	1	1	0
29_1	1	1	1	12
35_1	1	1	1	2
36_1	1	1	1	3

48_9	9	1	1	16
54_9	9	1	2	22
63_9	9	1	2	20
65_9	9	1	1	8
66_9	9	1	1	16
68_9	9	1	2	11
69_9	9	1	1	16
70_9	9	1	1	10
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1_10	10	1	1	16
10_10	10	1	1	5
15_10	10	1	1	6
16_10	10	1	1	9
24_10	10	1	1	15
29_10	10	1	1	16
30_10	10	1	1	21
32_10	10	1	1	11
33_10	10	1	1	12
38_10	10	1	1	7
39_10	10	1	1	8
40_10	10	1	1	11

15_19	19	2	1	14
16_19	19	2	2	21
17_19	19	2	2	26
24_19	19	2	2	22
25_19	19	2	2	24
26_19	19	2	2	22
31_19	19	2	2	28
36_19	19	2	2	21
37_19	19	2	1	16
39_19	19	2	1	13
4_19	19	2	2	17
40_19	19	2	2	30
41_19	19	2	1	12
43_19	19	2	2	20
45_19	19	2	2	24
52_19	19	2	2	29
54_19	19	2	2	31
60_19	19	2	1	9
61_19	19	2	2	21
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72_19	19	2	2	17
11_20	20	2	2	27
2_20	20	2	2	23
20_20	20	2	1	15
21_20	20	2	2	26
22_20	20	2	1	12
27_20	20	2	2	20
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37_1	1	1	1	2
38_1	1	1	1	0
42_1	1	1	1	6
44_1	1	1	1	0
46_1	1	1	1	6
53_1	1	1	1	6
56_1	1	1	1	0
58_1	1	1	2	21
64_1	1	1	1	2
7_1	1	1	1	0
70_1	1	1	1	6
73_1	1	1	1	4
74_1	1	1	1	2
75_1	1	1	1	2
76_1	1	1	1	2
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78_1	1	1	1	6
79_1	1	1	1	3
80_1	1	1	1	5
81_1	1	1	1	0
9_1	1	1	1	0
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11_2	2	1	1	0
20_2	2	1	1	19
26_2	2	1	1	3
27_2	2	1	1	8
31_2	2	1	1	2
33_2	2	1	1	0

42_10	10	1	1	16
43_10	10	1	1	14
46_10	10	1	1	8
48_10	10	1	1	7
49_10	10	1	1	11
50_10	10	1	2	21
52_10	10	1	2	20
53_10	10	1	1	12
54_10	10	1	1	17
56_10	10	1	1	10
58_10	10	1	1	18
60_10	10	1	1	9
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78_10	10	1	1	19
79_10	10	1	1	10
80_10	10	1	1	15
81_10	10	1	1	14

29_20	20	2	2	21
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30_20	20	2	1	20
32_20	20	2	1	13
36_20	20	2	1	22
41_20	20	2	1	13
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52_20	20	2	2	24
60_20	20	2	2	28
63_20	20	2	2	23
82_20	20	2	2	26
12_21	21	2	1	20
13_21	21	2	2	12
2_21	21	2	2	22
23_21	21	2	2	27
33_21	21	2	2	15
34_21	21	2	2	21
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38_21	21	2	2	19
4_21	21	2	2	23
40_21	21	2	2	26
41_21	21	2	1	14
44_21	21	2	2	23
67_21	21	2	1	17
72_21	21	2	2	18
8_21	21	2	2	17

34_2	2	1	1	6
37_2	2	1	1	6
39_2	2	1	1	3
40_2	2	1	1	5
41_2	2	1	1	0
46_2	2	1	1	3
51_2	2	1	1	3
52_2	2	1	1	6
53_2	2	1	1	7
54_2	2	1	2	25
56_2	2	1	1	4
58_2	2	1	1	5
59_2	2	1	1	10
59_2	2	1	1	8
60_2	2	1	1	2
63_2	2	1	1	2
65_2	2	1	1	1
65_2	2	1	1	1
66_2	2	1	1	2
66_2	2	1	1	10
69_2	2	1	1	6
70_2	2	1	1	5
72_2	2	1	1	1
73_2	2	1	1	7
74_2	2	1	1	7
75_2	2	1	1	0
76_2	2	1	1	4
77_2	2	1	1	5

11_11	11	1	1	14
18_11	11	1	2	22
20_11	11	1	1	19
21_11	11	1	2	14
22_11	11	1	1	13
26_11	11	1	1	18
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69_11	11	1	1	7
72_11	11	1	1	13
73_11	11	1	1	11
74_11	11	1	1	7
75_11	11	1	1	13
76_11	11	1	1	10

82_21	21	2	2	26
1_22	22	2	2	33
14_22	22	2	2	17
17_22	22	2	2	26
18_22	22	2	1	11
20_22	22	2	2	28
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55_22	22	2	1	13
63_22	22	2	2	25
7_22	22	2	2	21
71_22	22	2	1	12
82_22	22	2	2	27
9_22	22	2	1	14
9_22	22	2	1	14
12_23	23	2	2	21
13_23	23	2	1	8
19_23	23	2	2	20
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21_23	23	2	2	29
22_23	23	2	1	14
24_23	23	2	2	26
25_23	23	2	1	16
29_23	23	2	2	27
3_23	23	2	2	28

78_2	2	1	1	10
79_2	2	1	1	4
80_2	2	1	1	2
81_2	2	1	1	9
14_3	3	1	1	0
15_3	3	1	1	3
16_3	3	1	1	3
19_3	3	1	1	13
2_3	3	1	1	12
21_3	3	1	1	7
23_3	3	1	1	6
25_3	3	1	1	7
31_3	3	1	1	4
35_3	3	1	1	5
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38_3	3	1	1	1
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50_3	3	1	1	0
53_3	3	1	1	4
56_3	3	1	1	6
58_3	3	1	1	13
59_3	3	1	1	12
62_3	3	1	1	9
64_3	3	1	1	3

77_11	11	1	1	12
78_11	11	1	1	18
79_11	11	1	1	6
81_11	11	1	1	20
9_11	11	1	2	18
10_12	12	1	1	0
12_12	12	1	1	6
14_12	12	1	1	7
15_12	12	1	1	11
16_12	12	1	1	16
17_12	12	1	1	15
19_12	12	1	2	24
2_12	12	1	1	19
25_12	12	1	2	20
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35_12	12	1	1	6
40_12	12	1	2	23
42_12	12	1	1	16
45_12	12	1	1	14
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47_12	12	1	1	14
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55_12	12	1	1	12
56_12	12	1	1	7
57_12	12	1	1	5

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35_23	23	2	2	24
38_23	23	2	2	28
43_23	23	2	2	17
47_23	23	2	1	19
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67_23	23	2	2	26
7_23	23	2	2	18
71_23	23	2	1	14
82_23	23	2	2	25
12_24	24	2	2	19
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32_24	24	2	2	22
41_24	24	2	1	20
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71_24	24	2	2	23
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13_25	25	2	2	21
18_25	25	2	2	22
22_25	25	2	1	23
23_25	25	2	2	24
24_25	25	2	2	25
27_25	25	2	1	17

65_3	3	1	1	2
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66_3	3	1	1	1
68_3	3	1	1	5
69_3	3	1	1	0
70_3	3	1	1	6
73_3	3	1	1	2
74_3	3	1	1	1
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77_3	3	1	1	7
78_3	3	1	1	6
79_3	3	1	1	9
8_3	3	1	1	0
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81_3	3	1	1	7
82_3	3	1	1	5
9_3	3	1	1	6
10_4	4	1	1	6
12_4	4	1	2	21
15_4	4	1	1	8
16_4	4	1	1	0
2_4	4	1	1	12
20_4	4	1	1	3
26_4	4	1	1	8
29_4	4	1	2	22
30_4	4	1	1	18
31_4	4	1	1	1

59_12	12	1	1	18
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65_12	12	1	1	10
68_12	12	1	1	11
70_12	12	1	1	9
73_12	12	1	1	10
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79_12	12	1	1	16
8_12	12	1	2	23
80_12	12	1	2	24
81_12	12	1	1	17
11_13	13	1	1	18
20_13	13	1	2	24
26_13	13	1	1	11
27_13	13	1	1	14
29_13	13	1	1	12
32_13	13	1	1	18
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39_13	13	1	1	12
41_13	13	1	1	6
43_13	13	1	1	11
44_13	13	1	2	22

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33_25	25	2	1	11
34_25	25	2	2	27
44_25	25	2	2	22
45_25	25	2	2	26
57_25	25	2	2	24
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72_25	25	2	2	13
82_25	25	2	2	28
12_26	26	2	2	26
17_26	26	2	2	30
2_26	26	2	2	23
20_26	26	2	2	23
22_26	26	2	2	23
28_26	26	2	1	18
30_26	26	2	2	25
4_26	26	2	2	21
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12_27	27	2	2	21
19_27	27	2	1	14
21_27	27	2	2	26
22_27	27	2	2	23
43_27	27	2	2	29
47_27	27	2	2	18

34_4	4	1	1	10
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38_4	4	1	1	14
41_4	4	1	1	1
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43_4	4	1	1	10
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61_4	4	1	1	2
63_4	4	1	1	8
64_4	4	1	2	19
65_4	4	1	1	5
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67_4	4	1	1	6
68_4	4	1	1	7
69_4	4	1	1	10
73_4	4	1	1	6
74_4	4	1	1	0
76_4	4	1	1	6
77_4	4	1	1	2

47_13	13	1	1	9
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53_13	13	1	1	12
54_13	13	1	1	10
58_13	13	1	1	20
65_13	13	1	2	23
68_13	13	1	2	23
69_13	13	1	2	18
72_13	13	1	1	13
73_13	13	1	1	9
74_13	13	1	1	8
76_13	13	1	1	8
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78_13	13	1	2	20
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8_13	13	1	2	23
80_13	13	1	2	23
9_13	13	1	1	11
1_14	14	1	2	22
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22_14	14	1	2	27
23_14	14	1	1	19
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48_27	27	2	2	24
71_27	27	2	1	10
72_27	27	2	1	8
82_27	27	2	2	26
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28_28	28	2	2	18
32_28	28	2	2	22
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42_28	28	2	2	24
45_28	28	2	2	25
6_28	28	2	2	28
67_28	28	2	2	24
1_29	29	2	2	32
17_29	29	2	2	22
18_29	29	2	2	26
2_29	29	2	2	25
23_29	29	2	2	19
29_29	29	2	2	24
61_29	29	2	2	24
72_29	29	2	2	22
8_29	29	2	2	14
11_30	30	2	2	24
12_30	30	2	2	12
13_30	30	2	2	30

78_4	4	1	1	8
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81_4	4	1	2	12
1_5	5	1	1	7
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19_5	5	1	1	19
2_5	5	1	1	17
21_5	5	1	1	11
23_5	5	1	1	20
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29_5	5	1	1	15
30_5	5	1	1	11
33_5	5	1	1	7
35_5	5	1	1	2
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38_5	5	1	1	11
39_5	5	1	1	13
40_5	5	1	1	9
42_5	5	1	1	1
43_5	5	1	1	0
44_5	5	1	1	17
47_5	5	1	1	18
49_5	5	1	1	8

33_14	14	1	1	16
35_14	14	1	1	14
38_14	14	1	1	11
40_14	14	1	1	21
42_14	14	1	2	20
46_14	14	1	2	23
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51_14	14	1	1	20
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59_14	14	1	2	23
67_14	14	1	1	19
68_14	14	1	1	9
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15_15	15	1	1	15
17_15	15	1	2	24
19_15	15	1	1	16
2_15	15	1	1	17

14_30	30	2	1	10
19_30	30	2	1	11
20_30	30	2	2	24
21_30	30	2	2	22
22_30	30	2	1	17
24_30	30	2	2	24
27_30	30	2	1	21
33_30	30	2	2	21
34_30	30	2	2	26
4_30	30	2	1	9
48_30	30	2	2	24
5_30	30	2	2	27
61_30	30	2	2	25
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67_30	30	2	2	25
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29_31	31	2	2	28
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6_31	31	2	2	29
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82_31	31	2	2	27
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45_32	32	2	2	26
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61_7	7	1	1	10
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82_16	16	1	2	26
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58_17	17	1	1	11
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72_41	41	2	2	22
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45_43	43	2	2	27
71_43	43	2	1	12
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38_8	8	1	1	7
42_8	8	1	1	16
45_8	8	1	1	10
46_8	8	1	1	19
49_8	8	1	1	16
51_8	8	1	1	10

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67_17	17	1	1	10
72_17	17	1	1	12
76_17	17	1	1	15
8_17	17	1	2	18
1_18	18	2	2	25
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37_18	18	2	1	18
42_18	18	2	2	16
44_18	18	2	2	23

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4_62	62	2	2	22
4_63	63	2	2	27
6_67	67	2	2	29
6_69	69	2	2	33

APPENDIX B Anthropometric model results for Fg-net database

Image ID	Actual Age	Estimated Age
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13_0	0	3
15_0	0	3
19_0	0	3
22_0	0	3
23_0	0	3
24_0	0	3
25_0	0	4
26_0	0	3
30_0	0	8
31_0	0	3
35_0	0	4
36_0	0	5
37_0	0	3
38_0	0	2
40_0	0	10
41_0	0	3
42_0	0	3
43_0	0	3
46_0	0	3
48_0	0	4
50_0	0	3
51_0	0	3

Image ID	Actual Age	Estimated Age
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56_6	6	11
57_6	6	9
58_6	6	14
59_6	6	11
60_6	6	0
61_6	6	12
65_6	6	9
65_6	6	6
66_6	6	4
66_6	6	13
69_6	6	13
70_6	6	5
73_6	6	7
74_6	6	6
75_6	6	4
76_6	6	5
77_6	6	5
78_6	6	22
79_6	6	6
80_6	6	5
81_6	6	9

Image ID	Actual Age	Estimated Age
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68_13	13	22
69_13	13	21
72_13	13	23
73_13	13	17
74_13	13	11
76_13	13	9
77_13	13	11
78_13	13	25
79_13	13	15
80_13	13	26
1_14	14	21
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11_14	14	18
12_14	14	9
14_14	14	16
15_14	14	9
16_14	14	26
22_14	14	24
23_14	14	20
28_14	14	20
31_14	14	21
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Image ID	Actual Age	Estimated Age
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23_22	22	24
25_22	22	16
27_22	22	24
29_22	22	23
50_22	22	21
55_22	22	12
63_22	22	17
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13_23	23	13
19_23	23	26
21_23	23	26
22_23	23	18
24_23	23	24
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29_23	23	24
30_23	23	22

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57_0	0	3
58_0	0	14
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29_1	1	13
35_1	1	3
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65_7	7	11

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38_8	8	10
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49_8	8	17
51_8	8	13

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14_22	22	24
17_22	22	18

4_63	63	26
6_67	67	25
6_69	69	31

APPENDIX C New algorithm results for Private database

Image ID	Actual Age	Estimated Age
006_00	0	2
010_00	0	3
142_00	0	2
144_00	0	3
175_00	0	2
177_00	0	3
178_00	0	11
179_00	0	6
206_00	0	4
210_00	0	1
249_00	0	2
005_01	1	5
011_01	1	4
012_01	1	4
021_01	1	0
025_01	1	2
026_01	1	3
044_01	1	5
048_01	1	2
049_01	1	1
052_01	1	3
053_01	1	6

Image ID	Actual Age	Estimated Age
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141_05	5	3
150_05	5	10
151_05	5	9
167_05	5	11
169_05	5	5
172_05	5	14
175_05	5	12
176_05	5	9
178_05	5	8
185_05	5	6
199_05	5	10
200_05	5	4
202_05	5	7
234_05	5	8
247_05	5	5
251_05	5	12
252_05	5	3
003_06	6	10
006_06	6	8
007_06	6	6
009_06	6	8

Image ID	Actual Age	Estimated Age
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135_10	10	14
138_10	10	15
140_10	10	13
143_10	10	9
144_10	10	14
154_10	10	16
164_10	10	8
166_10	10	8
175_10	10	10
177_10	10	14
180_10	10	16
184_10	10	8
189_10	10	17
199_10	10	11
200_10	10	12
206_10	10	10
209_10	10	12
210_10	10	12
215_10	10	15
224_10	10	9
235_10	10	13

Image ID	Actual Age	Estimated Age
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157_16	16	14
165_16	16	12
167_16	16	16
170_16	16	15
172_16	16	16
179_16	16	13
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222_16	16	12
225_16	16	13
229_16	16	12
234_16	16	18
239_16	16	8
242_16	16	7
244_16	16	15
248_16	16	15

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069_01	1	4
071_01	1	1
075_01	1	5
077_01	1	4
078_01	1	2
090_01	1	2
099_01	1	3
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103_01	1	2
104_01	1	6
114_01	1	4
115_01	1	2
119_01	1	5
120_01	1	1
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123_01	1	1
124_01	1	3
132_01	1	2
137_01	1	2
138_01	1	5
144_01	1	3
164_01	1	3
168_01	1	2
169_01	1	2
172_01	1	4
174_01	1	2

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049_06	6	15
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063_06	6	12
065_06	6	7
085_06	6	8
086_06	6	9
103_06	6	8
112_06	6	9
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201_06	6	10
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022_07	7	9
026_07	7	17
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070_07	7	7
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073_07	7	12
076_07	7	17
084_07	7	12
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237_11	11	12
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003_12	12	8
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073_12	12	16
074_12	12	14
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Curriculum Vitae

Petra Grd was born on February 14th 1986 in Kutina. She finished elementary and high school in Kutina and graduated from the Faculty of Organization and Informatics in 2009, where she finished her PhD in 2015. Since 2009 she has been working at the Faculty of organization and informatics as a research assistant on the project "Methods of evaluation of biometric characteristics" and as a teaching assistant at for the courses "Selected Topics in Biometrics" and "State and Administrative Information Systems" at the undergraduate level, "Internet Security" on graduate level, and "Business use of biometric technology" and "Business information systems of state administration". Her research interests are related to biometrics, specifically face biometrics and facial aging. Other than research and teaching, she was the secretary of the Disciplinary Tribunal and the Association of associates, a member of various committees, and a member of the Student council. She has published several scientific papers and participated in conferences and summer schools at home and abroad.

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