Age Estimation from Rhytides using Machine Learning

CS766 Computer Vision

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ABSTRACT

Age estimation from face images is an active research area [1], with applications ranging from facial aging simulation to security, surveillance, and biometric data. Various aspects of human faces change as we age. In children, head shape changes rapidly as the skull and jaw develop. In adults, head and facial hair color and density change, skin blemishes may appear, and rhytides (facial wrinkles) often develop as a result of the breakdown of collagen in the skin. Age estimation can be difficult and imprecise, as environmental and genetic factors affect aging rate and make perceived age vary greatly among individuals. Many studies use distances between facial landmarks for age estimation [2] used a Sobel edge magnitude to extract wrinkle density and depth from face images for age estimation, but this work did not differentiate types of wrinkles in different parts of the face. Other recent work has focused on global methods including deep learning on face image sets. Our aim of this project was to study and experiment with age estimation techniques and computer vision with the idea of more discretized learning datasets using rhytide vectors categorized by type and magnitude for each type.

CCS CONCEPTS

- Computing methodologies → Machine Learning → Cross-validation
- Mathematics of computing → Mathematical analysis → Functional analysis → Approximation

KEYWORDS

Facial detection, Facial Recognition, Age Estimation, Machine Learning, Computer Vision, Image Processing, Classification

1 INTRODUCTION

Age estimation from face images is an interesting research area which has been explored in prior work (such as [3], [4], [5], and [6]), but estimation accuracy from these studies remains low – around 80% to 86%, no better than human accuracy [7]. Facial detection and facial recognition systems have improved dramatically in recent years by using deep neural networks, but such approaches provide little insight into the underlying features being used to detect and recognize faces in images. Moreover, they typically do not provide age estimates. We believe that rhytides are a logical and easily derived feature space important to age estimation applications. Specifically, we are interested in this problem for several reasons. First, the problem is of general interest to the public. Second, our proposed work is a new direction in an existing field which means we can easily measure performance of our approach compared to existing prior methods. Finally, even if our method does not result in better age estimation accuracy, we can still present qualitative analysis and examples, such as distribution and intensity of different wrinkle types (rhytides) by age, gender, and race.

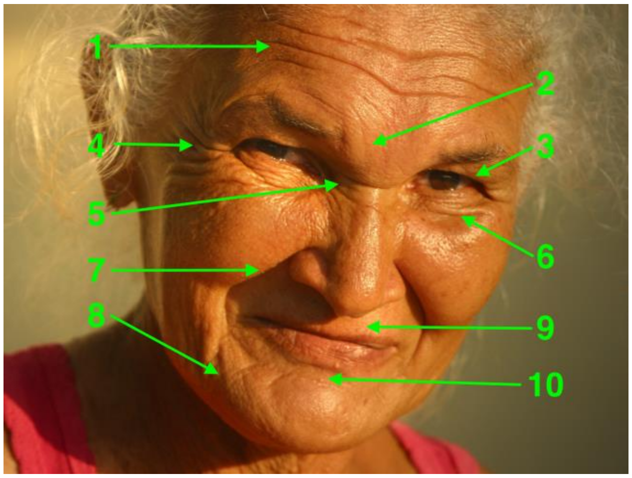

Figure 1 – Rhytide labels

In this project (as shown in Figure 1), we focus on age estimation based on specific types of rhytides as they appear in different parts of the face:

(1) Forehead lines
(2) Glabellar frown lines
(3) Upper eyelid hooding
(4) Crow's feet (outside corner of eyes)
(5) Bunny lines (inside corner of eyes)
(6) Bagging of lower lids
(7) Nasolabial folds (laugh lines)
(8) Marionette lines (jowls)
(9) Lip lines (vertical lines on upper and/or lower lip)
(10) Mental crease (between chin and lower lip)

For this we have used existing face detection software (OpenCV) to detect faces in an image, then we use edge detection in specific regions of the face image to identify and quantify the presence on the aforementioned types of rhytides. With this as our feature set, we will process existing datasets (such as [7], [8], or [9]) of age-labeled face images to study the distributions of each rhytide type by age and gender. We then train a simple Machine Learning (ML) model to predict age from these rhytide measurements, and finally we compose all these steps into an age-prediction pipeline.

Some of the challenges in developing such a system included: Image quality issues such as poor lighting, or low-resolution images. We attempted to avoid this problem by studying only high-quality face image data training sets. Facial expressions in the image can also change the appearance of rhytides (a smiling, angry, or surprised face show different wrinkles than a neutral one) We considered the possibility of classifying emotion of the face images first and then weighting the rhytide intensities differently for each emotion but we did not end up implementing this idea. The last problem which we noticed when approaching this idea, which interferes with our data, was makeup or facial hair obscuring and occluding some rhytides.

2 RELATED WORK

Age estimation research has gained significant attention in recent years with many different approaches and goals for the application of computer vision and machine learning. Age can be determined as either an actual age, appearance age, perceived age, or estimated age. Additionally, there are many such application areas for age estimation techniques which makes it a popular subject matter in computer vision research. Some of these application areas include: Age simulation, Customer relations, Security and surveillance, Biometrics, Employment, Content Access, and Missing Persons. [1]

In a recent article exploring age estimation. They used facial anthropometry (scientific study of measurements and proportions of the human body) and determined features to used based on distances to pre-defined landmarks as well as facial shape. [3]

Some more recent work in this subject has utilized aspects of machine learning and artificial intelligence to aide in the process of tackling this multi-class classification problem. [11] Some of the difficulty in estimating age based on image data is facially prescient as we know intuitively that not everyone ages the same and people of different ethnicities all experience aging differently. This is why determining and predicting aging patterns is part of the related work in our research. A study was done to determine an aging pattern subspace by using temporal images labeled in order and training an estimation model with enough of such images. [12]

3 OVERVIEW

This section is used to provide a high-level overview of our proposed system for estimating age based on rhytide classifications. We review the process of our system and some of the face image datasets we tried and what we determined when using them.

3.1 Age Estimation

For our age estimation process we set out to determine and estimate age using facial rhytides (wrinkles) as is a common human perception of older people. It is a natural heuristic to determine someone's age based on their visual signifiers of age such as wrinkles. Similar to other papers in the related work we sought to determine another potentially useful methodology for both estimating age as well as creating data points that are much more easily interpretable by someone who is not well versed in the realm of machine learning. Our desired feature set was to classify different sections of rhytides and assign a weight or number associated with the number of edges in the region. The process we decided on using to estimate age using our rhytide vectorization started with reading in image data from age-labeled datasets. After we have extracted the feature vector for each image, we use them in a machine learning model to find a correlative prediction model for classification. Following the traditional training / testing breakdown of 80/20, where 80% of the image data is used to train this K-Nearest Neighbors (KNN) model [14] and the leftover 20% is used to test and evaluate the trained model.

3.2 System Overview

Our methodology for estimating age utilized Python Open-Source Library OpenCV and we applied their pre-defined Haar feature cascade filter to determine facial landmark locations. Haar features are used as a way to quickly traverse a decision tree of classifiers trained to detect facial features.[13] For our Haar facial model we used the built-in pre-trained model available as a part of OpenCV called "haarcascade_frontalface_alt2.xml". From these landmarks determined in the pre-trained model 67 landmarks in total.

Figure2 – Preliminary results using our methodology

Figure 2 shows some preliminary results which we felt were promising in utilizing our methodology of estimating age based on facial wrinkles (rhytides). As you can see the total number of detected wrinkles increases as the relative age of the facial image increases.

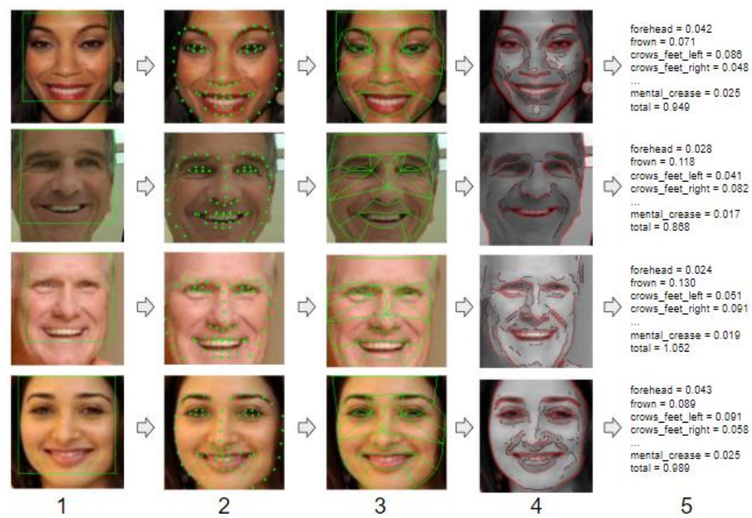

Figure 3 – Methodology and process of our system

Figure 3 details our image processing pipeline for analyzing image data and producing our labeled vector of rhytide quantization. We start by using Haar cascades to recognize the face in the image data. Then we detect and mark the landmarks in the face using Open CV's local binary feature detection from a pre-trained model. After we have determined and detected the facial landmarks, we use these points as vertices for partitioning the facial data into polygonal regions associated with each of the separate rhytides in our feature space. An example of such annotated features can be seen below in Figure 4.

{'forehead': 28, 'frown': 30, 'upper_eye_hood_left': 12, 'upper_eye_hood_right': 13,'crows_feet_left': 32, 'crows_feet_right': 36, 'bunny_lines_left': 14, 'bunny_lines_right': 15, 'bags_left': 8, 'bags_right': 9, 'laugh_lines_left': 15, 'laugh_lines_right': 15, 'jowls_left': 10, 'jowls_right': 11, 'lip_lines': 4, 'mental_crease': 8}

Figure 4 – Feature vector information

These features are determined by taking each individual polygonal region extracted from our previous step and then by applying a small Gaussian blur we remove noise in the image data region. After this blur is applied, we utilize a Canny edge detection in each polygonal region at several levels of thresholds to quantify the amount and intensity of wrinkles in that particular region. The feature vector we used for each image was based on a weighted sum of the edge pixel counts normalized to the polygonal area.

4 Using Age-Labeled Datasets

In order to develop a machine learning model to train and extract rhytide features we utilized publicly available face image datasets. We explored several of these face image datasets. The UTKFaces face image dataset [7] contained 23,708 images all labeled with gender, age, and race (encoded in their file names). These images were all uniform in size (200x200 pixels) It contained mostly head-on views of the people, but some of the quality we found to be poor (grainy or washed-out images) Running our facial landmark detection on this dataset we identified faces in 72% of the dataset as a rate of 2.1 secs/image. Another dataset we considered using in this project was the IMDB-WIKI dataset [8]. This contained 460,723 images from IMDB (actors), and 62,328 images from Wikipedia (celebrities). The dataset included gender and age for each image, but not race. (details contained in .mat files). The images in this dataset varied in size, most were at least 200x200 pixels but some were much higher. A sample of the images were poor in quality, included multiple faces, were side-view of the face, or were even just a cartoon. Running our facial landmark detection on this dataset identified 61% of the Wikipedia images and 70% of the IMDB images as faces. Since the disparate sizes of the IMDB-WIKI dataset would cause issues when trying to apply this to a machine learning process, since they would not be uniform in size / scale we decided to utilize the UTKFaces dataset.

Figure 5 – Sample of UTKFaces image data

Figure 5 shows a sample of images from the UTKFaces dataset. As shown you can see faces of many different ages, genders, and races were represented in this dataset. It was also quite helpful for us that this dataset contains mostly images with head-on views of their subjects.

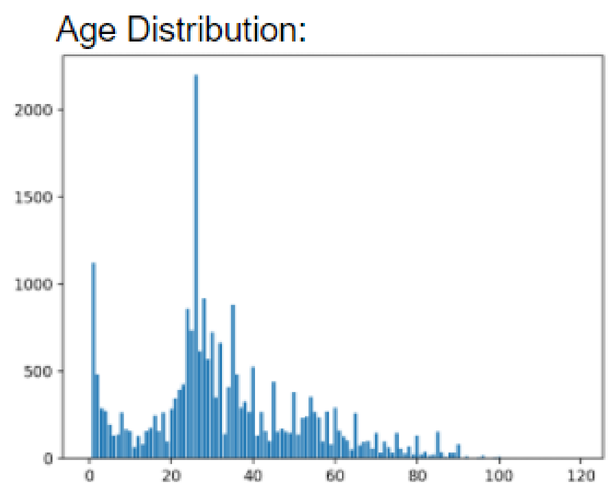

Figure 6 – Age distribution of UTKFaces

We also determined the age distribution of this dataset as shown in Figure 6. Most of the ages of the faces present in this dataset were between the ages of 20 and 40 years of age.

However, even though this dataset provided each of the images at the same size, some problems were noticed when we were evaluating our system. We noticed that quality of these images varied. We also suspected that our edge detection method for finding wrinkle information was hindered by occlusions such as watermarks, glasses, hair, face paint, facial hair, hats, and facial jewelry.

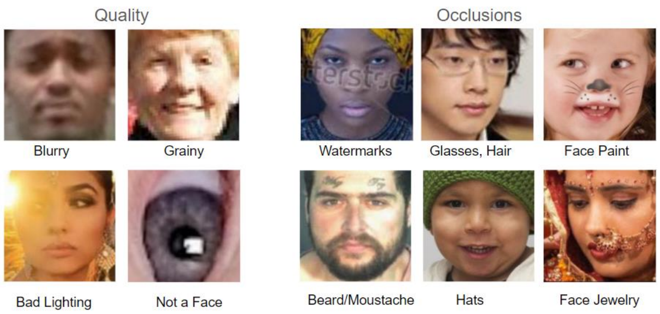

Figure 7

As shown in Figure 7 here is a sample of some of the images we found as culprits for providing erroneous data to our training model. Blurry, grainy, bad lighting, and images that simple did not contain a face are some such examples of found images that were of poor quality for our training model.

5 IMPLEMENTATION

This section is used to present some of the details of our current system for estimating age based off of rhytide features and parts of the project we think we could improve on.

5.1 Rhytide Segmentation

For creating the polygonal regions used to divide our facial image data into categorized rhytide sections we took the face landmark points and created an index used to collect the points which defined each of the separate regions for the facial rhytide segmentation to occur in the regions we cared about. After defining these indices on the polygon points, we then separated out the image data into these polygonal regions and used those as masks to our edge detection and feature spaces vectorization. In order to use our facial data in a more uniform fashion we additionally used the facial landmark data of the eyes to both rotate and crop the image more strictly around the face. This helped to make both the position and scale of the facial data more correlated when taking this further into our age estimation methodology.

5.2 Machine Learning Model

For our machine learning portion of this age estimation system. We first read in the resulting values of the prior steps in the pipeline then we randomly assign 80% of the data to be used as training data and the remaining 20% to be tested against the resultant trained model. We then fit a K-Nearest Neighbors model [14] on the training data consisting of all the feature vectors of rhytide information. We used a neighbor size of 15 and the built-in ‘ball-tree’ algorithm from the sklearn python module. Once this model has been trained, we evaluate the distances of the testing set from their ground truths. We compare average ages corresponding to the nearest neighbors versus the true age. We then plotted histograms of these values and started to evaluate our results.

6 EVALUATION

In evaluating our results, we unfortunately came to the conclusion that our model and methodology either was not robust enough to be used in estimating facial age based on image data or that there were problems in our process pipeline.

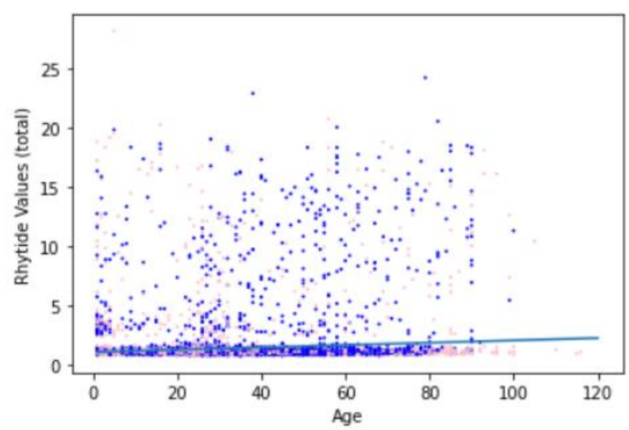

Figure 8 – Initial results (slope of best fit line is 0.00993)

From our first test results, as shown in Figure 8, we detected faces in 69% of the images. We had a wide range of rhytide estimates from our polygonal segmented edge detection process. We did see a slightly positive correlation between age and rhytide measurement values.

As was discussed earlier and shown in Figure 7 we decided to spend the time to clean our training image dataset and remove any images we felt could be causing an error to persist in our training model. This consisted of pruning any of the facial image data that was poor in quality or contained facial occlusions. Our resultant dataset then contained 2,555 faces which is 10.8% of our original UTKFaces dataset.

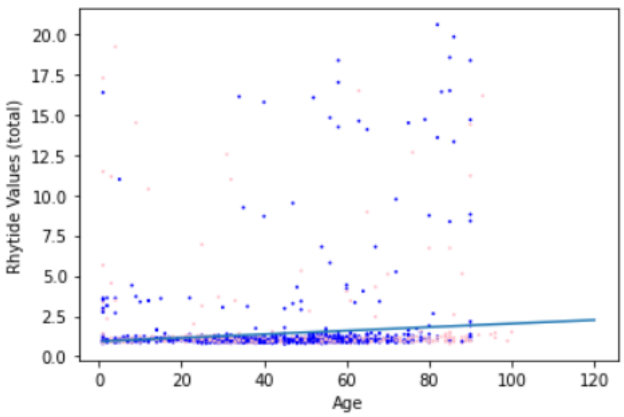

Figure 9 – Fewer outliers (slope of best fit line 0.01101)

When testing this new subset of our initial training dataset we saw a slight increase in the correlation. We now detected faces in 79% of the images, had a smaller range of rhytide estimates for all ages, and a higher positive correlation between age and rhytide measurement values. The features we were able to determine had the strongest correlation from this round of evaluation were the frown lines and bunny lines. However, this result also felt unsuccessful.

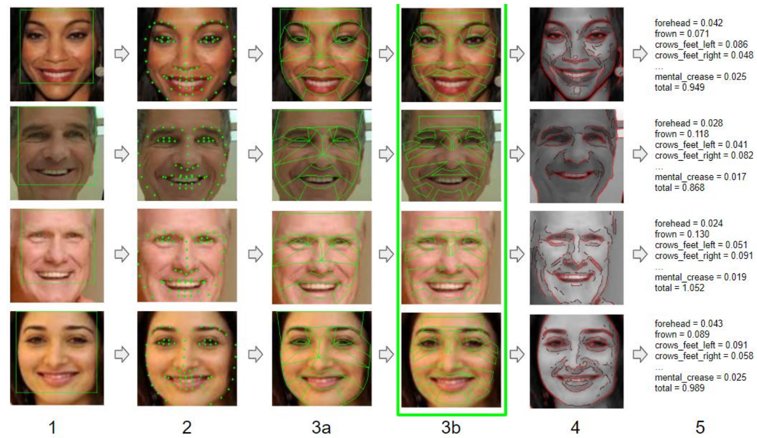

Figure 10 – Revised method (Shrinking polygonal segmentation)

The next change (as shown in Figure 10) we implemented in evaluating our process to refine for better results was to shrink the polygonal areas to avoid erroneous edges detected such as: lips, hair, facial outlines, and other non-rhytide edges.

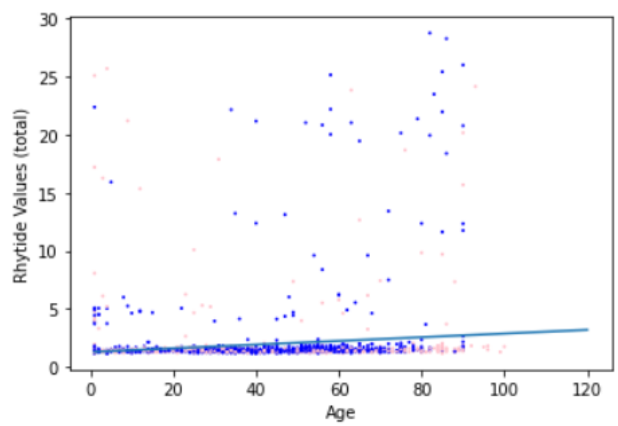

Figure 10 – Revised method results (slope of best fit line is 0.01588)

In these revised results with a slight change to our process, we see slight improvement over the cleaned dataset evaluation. In this iteration of the model nearly all of the rhytide features contribute equally in correlation to their predictive weight. But once again this is an unsuccessful evaluation of our model.

7 CONCLUSION

In conclusion, while trying to devise a methodology for discerning more interpretable data into a model for predicting and estimating age based off of facial image data. We have found that at least with our current system rhytide feature vectors are a poor analog for solving the problem of classifying image data based on age. While it is still an interesting problem and there is plenty of other things we could try, we stopped after attempting to change our project pipeline and shrink the feature extraction polygonal segments. Another change we could make to solve for poor performance could be to adapt our feature set to a different model of machine learning. There may also be a different machine learning model that works better for this application. We did, however, find nominal increases in correlation with every revision to our training model when attempting to solve for errors found in our evaluation step.

Some of what we learned throughout this effort was: measuring rhytides is difficult in “real world” images. Image quality, occlusions, lighting, and facial expression cause a large amount of variation in the feature space of rhytide measurement using a Gaussian blur and Canny edge detection. A highly-controlled dataset of labeled image facial data would be more useful in controlling for the independent variables at play in such a variable environment. Ultimately, we have learned through this project that age estimation is a difficult problem at hand.

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