Facial Wrinkles Detection Algorisms: A Review

Remah Mutasim Ibrahim Albashir
College of Computer Science and Information Technology
Sudan University for Science and Technology, Khartoum, Sudan
Email: remah.mutasim.i@gmail.com

Abstract: Aging is a natural phenomenon that affects the human body, where the most important features that occur according to the progress of age are facial wrinkles, which are the focus of this paper. Wrinkles detection plays an important role in facial analysis. Some wrinkles detection algorithms achieved good results like Gabor Filter, Hybrid Hessian Filter and Hessian Line Tracking, but further enhancements needed in this research area. The purpose of this paper is to summarize the state-of-the-art wrinkles detection methods in the past ten years. A comprehensive literature review on manual and automatic wrinkles detection techniques will be presented in this paper. Furthermore, we present four state-of-the-art datasets that can be used for wrinkles detection evaluation. We discuss the performance metrics for wrinkles detection algorithm, and conclude the paper by addressing future direction.

Keywords: Facial Wrinkles, Automatic Wrinkles Detection, Gabor Filter, Hybrid Hessian Filter, JSI.

I. Introduction

Factors like aging and frequent exposure to solar (UV) radiation are affecting the face features. These factors contribute to change of facial skin, and the overall face shape will be affected by these changes in addition to features changes of the face: folds, wrinkles, and lines will be apparent and become more obvious with age. These wrinkles are changed based on the skin nature and muscle contraction. Wrinkles can be defined as creases or small furrow in facial skin that caused by expressions or age. Ekman et al. described wrinkles as a line with depth and sometimes the line have a width more than surface line. In some faces, the wrinkles may be temporary appear with certain actions, while other faces may show permanent wrinkles and it will be deepen with certain actions. In 2D images, the wrinkles are affecting the skin; it creates deep creases and sometimes creates curvature in the skin surrounding, this curvature will affect the overall facial skin. The wrinkles characteristics can be described using two major factors: one of them used to define the location of wrinkles curve lines, this called furrow or macro, and the other one is bulge, which is used to give curved surface shape. Wrinkles where it considered as temporary wrinkles, but may become permanent with time. The latter is permanent wrinkles which are appearing with age. Furthermore, as mentioned in, the wrinkles can be divided into four types according to wrinkles pathogenesis and histological conditions. First type is atrophic; these types of wrinkles appear as parallel lines and they disappear when skin is put under transversal tension. Second type is elastic; this type is appearing when the skin is exposing to sun and it considered permanent. Third type is expressional, as mentioned above, it is temporary wrinkles, but it may become permanent lines. Fourth type is gravitational; it resulted from gravitational forces inducing folding and sagging of skin which has lost its turgidity.

Human eye can detect wrinkles easily, but it is a very difficult task to detect wrinkles automatically using image processing techniques. This is due to the wrinkles shape is varying according to ethnic group, gender, age, and personality style. Also, it depends on the image quality that was affected by image acquisition environment. Many different approaches in detecting the features changes on the face exist, including detection of facial wrinkles. Earlier work in wrinkles detection was proposed by Lodén et al. They used silicone to produce the facial wrinkles by making replica using this silicone and made the measurements depend on it. But these old studies were not efficient enough, because it is very difficult to get silicone replicas same as the actual skin morphology. In 2014, Ng et al. proposed Hybrid Hessian Filter (HHF) to detect and quantify the facial wrinkles automatically; their algorithm recorded very good results in detecting wrinkles.

As automatic wrinkles detection became an important step in many applications, we aim to provide a review on manual and automatic state-of-the-art wrinkles detection techniques to provide a breadth and depth analysis. In addition, many datasets were used to develop and evaluate these methods, therefore, a review on datasets is important. Moreover, the evaluation methods that were used to measure the performance of wrinkles detection methods will be presented in this paper.

This paper is organized into the following sections: Section 2 presents the application of wrinkles detection algorithm. Section 3 describes four state-of-the-art datasets that can be used for facial application. Section 4 explains the performance measurement methods that can be used to evaluate the wrinkles detection methods. Section 5 and 6 show comprehensive explanation about manual and automatic wrinkles detection algorithm. Finally, conclusion and future direction will be presented in Section 7.

II. Applications of Wrinkles Detection Algorithm

Facial wrinkles are very important facial feature that present on aging faces. Accurate wrinkles detection plays an important step in several image based applications, like age estimation. [x] [xii],

References:
and synthesis [xiii], face modeling [xiv], facial expression recognition [xvi], and it can be used as soft biometric [xvii]. In the age estimation and synthesis application: different parts of human body are being affected by human age under several environmental and biological factors. The wrinkles are the obvious change that occurs on the face according to the age. So wrinkles detection is main stage in many studies of age estimation [xvii] [xviii] [xix] [xx] [xxi]. Also wrinkles can be added to facial image to show how it can affect on the face in case there are some changes occurs like gain weight or loss weight as mentioned in [xii].

In the face modeling application, Bando et. al. [xiv] used fine and large scale wrinkles to model the human skin including facial skin; they found that the wrinkles are adding more realism on the facial skin.

In facial expression recognition application, Huang et. al. [xv] claimed that different types of wrinkles like forehead, nasolabial, dimples, chin furrows and eye pouches are important features that can reflect individual’s emotion. In their experiments they proved that nearly 70% of expressions can be differentiating by skin wrinkles and slide view profile. This result contributed to increase the overall recognition rate. So the facial wrinkles can be used as one of the features that can increase the recognition rate. Many studies used wrinkles for this type application as mentioned in [xxi] [xv] [xxiii].

In soft biometric application, soft biometric is a feature that been used to complement the primary biometric features, such as fingerprint, face, iris, and hand geometry, to enhance the performance of a primary (hard) biometrics system [xxiv]. The researcher tried to investigate the discriminative power of using wrinkles as soft biometric as proposed by Batooll and chellappa in [xvi]. In addition to all these applications the facial wrinkles detection is important step in facial retouching application as mentioned in [xxv] [xxvi] [xxvii].

III. Face Datasets

Different types of face datasets are available, but only a few of them are appropriate to be used in developing an accurate wrinkles detector, here are the four most popular state-of-the-art datasets:

A. FG-NET Dataset

FG-NET is a big dataset consists of 1002 images taken from 82 different subjects with ages ranged between 0 to 69 years old; these images were collected from albums using scanner, most of the dataset images were 40 years [xxviii]. This dataset is not clear and the images resolution was different, so it is not a good choice for wrinkles detection algorithm. The dataset images comes along with many information like age, and each image had several copies with different age, so it can be used for age estimation application as used in [xix] [xxix].

B. Bosphorus Dataset

Bosphorus is expression dataset contained 3D and 2DFaces [xxx]. This dataset is highly resolution dataset because it collected under controlled environment from different 105 subjects; ages among most of them were ranged between 25 and 35. The dataset considered as excellent choice for wrinkles detection algorithms, it used by Ng et. al in [iv][ix] and it recorded very good results.

C. FERET Dataset

FERET is a large dataset consists of two categories; one of them is used for development, so it is available for researcher, while other category is isolates and reserved for test the facial recognition algorithm [xxxi]. When compare the resolution of FERET dataset to FG-NET, FERET is considered better resolution than FG-NET because it collected under controlled environment. It used by Ng et al. [ix] to assess the performance of their algorithm for wrinkles detection.

D. MORPH Dataset

Morph is a large dataset consisted of 55,134 images collected from more than 13,000 individuals with ages ranged between 16 to 77 years old. The dataset is available for a researcher who works on age progress applications. Morph also considered as low resolution dataset like FG-NET, because it collected from scanning photographs, but it contained older age photos, so it may considered a good choice for wrinkles detection algorithms if the resolution adjusted and the noise removed [xxxii].

Table I: Summary of The State-of-the-art Face Datasets.

<table>
<thead>
<tr>
<th>Datasets</th>
<th>Number of Subject</th>
<th>Number of Images</th>
<th>Age Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bosphorus</td>
<td>4666</td>
<td>105</td>
<td>25 - 35</td>
</tr>
<tr>
<td>FG-NET</td>
<td>1002</td>
<td>82</td>
<td>0 - 69</td>
</tr>
<tr>
<td>FERET</td>
<td>2366</td>
<td>994</td>
<td>10 - 70</td>
</tr>
<tr>
<td>MORPH</td>
<td>55,134</td>
<td>13,000</td>
<td>16 - 77</td>
</tr>
</tbody>
</table>

IV. Performance Measurements for Wrinkles Detection Algorithms

Two measurements to evaluate the performance of the wrinkle detection algorithm mentioned in the literature, which are Jaccard Similarity Index (JSI) that was first used by Ng et al. [ix] in wrinkles detection to evaluate the performance of their algorithm. Another measurement is mathematical evaluation setup that proposed by Batool and Chellappa [xxiii]. JSI is the most commonly used method in medical imaging analysis, this techniques originally introduced by Paul Jaccard [xxiv], which also known as Jaccard similarity coefficient or intersection over union. The mathematical form of JSI is:

\[
JSI(A, B) = \frac{A \cap B}{A \cup B}
\]

Where A and B are two compared images. Second method was proposed by Batool and Chellappa [xxiii]: they proposed evaluation setup to assess the performance of their wrinkles detection algorithm. Three terms were used in this evaluation setup: detected, original and well-localized. The term detected considered the output wrinkles from the algorithm, while the term original refer to the original wrinkles those were hand-drawn by user, and well-localized term refer to wrinkles that detected at correct locations. Detected wrinkle is considered...
well-localized if it is lies within the distance of m pixels (m=3) from the hand-drawn wrinkles. They used morphological dilation with margin m to define the overlap area. Detected wrinkle is considered well-localized if it lies within the overlap area. The following ratios were proposed for evaluation:

- Detection Ratio ($r_{detect}$): The ratio of the total length of original wrinkle within the overlap region of detected wrinkles to the total length of the original wrinkles.

$$r_{detect} = \frac{\sum_{n_w} L_{overlap}}{\sum_{n_w} (L_{overlap} + L_{miss})}$$

- False Alarm Ratio ($r_{false}$): The ratio of the total length of falsely detected wrinkles to the background area with no wrinkles (S) represents the measure on image space.

$$r_{false} = \frac{\sum_{n_p} L_{false}}{v(s) - \sum_{n_w} L_{original}}$$

- Miss Ratio ($r_{miss}$): The ratio of the total length of missed original wrinkles to the total length of original wrinkles.

$$r_{miss} = \frac{\sum_{n_p} L_{false}}{\sum_{n_w} (L_{overlap} + L_{miss})}$$

Where $r_{miss} = 1 - r_{detect}$ and $n_w, n_p$ are the total number of hand drawn and detected wrinkles respectively.

V. Manual Wrinkles Detection

Wrinkles considered as important facial features that affects on human age estimation, so it is important in several facial applications related to aging applications like age estimation [x][xii] and synthesis [xiii], facial expression recognition [xv], face modeling [xiv], and can be used as soft biometric [xvi]. Earlier wrinkles detection studies used manual techniques to detect facial wrinkles and other facial features. Using silicone material is one of these manual techniques, the silicone material is used to produce skin replica, then use this replica to detect the wrinkles as mentioned in [viii] [xxv] [xxvi]. The drawbacks of this approach represent in the difficulty to produce silicone replica same as actual skin morphology, in addition to the silicone material problem itself. Also the cosmetics science has some techniques for facial wrinkles detection, one of them is using three dimensional optical profilometers based on digital morphology as mentioned in [xxxvii][xxxviii], the limitation of this approach represents in equipment resolution. Another type of manual wrinkles detection is human observation as proposed by Mark et al. [xxxix], their work was examination of several feature’s influence on human age judgments by drawing the profiles of different male’s ages, then to determine the age of drawing wrinkles faces.

Aznar-Casanova et al. [xli] presented a study to determine if the facial age is affected by wrinkles, their study composed of two experiments: In experiment I; categorical age judgments for males and females had been made. This experiment examined by ninety nine volunteers (male and female) segmented to three age categories (preadolescents, young adults, and middle-aged adults). The result of this experiment indicated that the influence to age will be greater if the number of wrinkles and the depth furrows are increased. In experiment II, the participant compared between each pair of faces to determine the similarities of features that had more effects on the face. The results showed that the wrinkles’ number had more influence on age of the face than the wrinkle type.

Batool and Chellappa [xvi] conducted a study to determine if the facial wrinkles could be used as soft biometrics, their experiments based on manual wrinkles detection.

VI. Automatic Wrinkles Detection

The great improvement in computer vision motivates researchers to spot light on multiple algorithms like automatic wrinkles detection algorithm that considered as important step in many applications like age estimation application [x], where fine lines and wrinkles play an important role [xli]. Kown and lobo [xii] tried to show how wrinkles affect on human age based on three age groups; which are babies, young adults, and senior adults. Firstly, they detected the primary features of each face: like eyes, nose, mouth, chin, and virtual top of the head, the output was distinguished the baby from others. Secondly, the facial wrinkles was detected using wrinkles geography map, then the output distinguished the seniors adults from younger adults categories. On the other hand, Choi et al. [x] proposed wrinkle representation scheme to estimate age of the skin by construct skeleton consisted of most features related to the wrinkles using watershed algorithm to represent the wrinkles on skin of the image.

The above mentioned studies tried to identify the effect of facial wrinkles on human age, but there are researchers just focused on developing algorithms to detect the wrinkles automatically. Table 2 and Figure 1 depict the development of automatic wrinkles detection methods over the past 10 years in chronological order. Cula et al. [xlii] developed automatic wrinkles detection algorithm, it was based on orientation estimation and the frequency of elongated spatial features. They used a set of facial images that was clinically validated to detect the wrinkles that appear on the forehead, the wrinkles scale for these images was varying from 0 (no wrinkle) to 11 (most severe wrinkles). The algorithm was tested using two cases: First they combined the wrinkles depth information with the wrinkles length information, and second they separated the wrinkles length information from the wrinkles depth information. The algorithm performed better in the first case. This algorithm considered as one of the earliest automatic wrinkles detection algorithms in 2D images, but it has some
limitations in wrinkles localization, and in distinguishing wrinkle from image noise like hair, scars or illumination.

After Cula et al. [xiii], other researchers tried to improve the quality of automatic wrinkles detection methods. Ng et al. [ix] developed a novel method for automatic wrinkles detection, it called Hybrid Hessian Filter (HHF). HHF is an algorithm for automatic wrinkles detection in 2D facial images. The algorithm is based on Hessian matrix and directional gradient which is used to detect the facial wrinkles by computing this matrix to all pixels for each image, the Hessian Matrix maximum eigenvalues indicates whether or not the point is a part of a ridge regardless this ridge’s orientation. Each point (x, y) fields second derivative component measures eigenvalues (independent vector), the more small eigenvalues, the more fields corresponding eigen-direction change a little and vice versa. HHF used 100 random selected images from Bosphorus dataset [xxx], from these images, researcher used forehead area, so they cropped the images manually with rectangle selector. The algorithm was showed better result compared to other methods such as Cula’s method [xii], it considered outperformed state of the art methods with average JSI of 75.67%. According to this result, HHF considered as a strong wrinkles detection algorithm compared to other state-of-the-art methods, it had a good result regarding wrinkles localization in addition to increasing the correctly detected wrinkles’ number. HHF recorded very good result for forehead especially medium and coarse wrinkles, but, more effort is needed to improve this algorithm, it neither detect wrinkles on other facial regions nor detect vertical lines.

As an extension to HHF, Ng et al. [iv] developed Hessian Line Tracking (HLT), tried to overcome the problem of previous automatic wrinkles detection methods. HLT is an algorithm for automatic wrinkles detection in 2D facial images, it composed of hessian seeding and directional linetracking. HLT executed in many steps; firstly HHF was used to extract the seeds and then the optimum pixels for starting point determined. Line tracking was used to determine each pixel belongs to the wrinkles line. Then post processing using median and directional filter in addition to area thresholding was applied to remove the noise (outlier). The algorithm was validated using 100 manually cropped forehead faces from Bosphorus dataset [xxx]. when HLT compared to benchmark algorithms like Cula’s algorithm [xii], Frangi Filter (FRF) [xiii] and HHF [ix] it performed better result with accuracy of 84.00%. HLT considered a strong detector of forehead wrinkles in 2D images, add to that, the algorithm has ability to explore the curve and valley pattern in order to wrinkles connectivity, but it needs more enhancement to detect other facial wrinkles and vertical lines.

More recently, Ng et al. [xliii] have proposed to use wrinkles complementary features for face age estimation. They proposed two new methods in this study, Multi-scale Wrinkle Patterns (MWP) used as a feature representation for facial wrinkles and Hybrid Ageing Patterns (HAP) used as a new feature representation for face age estimation. HLT [iv] was used as wrinkles detector in MWP after tested against state-of-the-art wrinkles detection methods (HHF [ix], Cula’s method [xii], and Batool’s method [xii]) to detect whole facial regions. Lastly HAP is used to train the SVM to estimate the facial age. Three state-of-the-art dataset (FERET [xxxi], FG-Net [xxviii], and Morph [xxxi]) were used to assess the performance of HAP, it recorded good result with a MAE of 3.68 (_2.98) on MORPH.3.02 (_2.92) on FERET, and 5.66 (_5.88) for FG-Net.

Batool and Chellappa proposed many algorithms for facial wrinkles detection [xxxii][xxvii][xlii]. In 2012, they proposed a novel modeling technique for wrinkles, based on spatial marked point processes (MPP). They considered the wrinkles sequences of segments of line that appear as stochastic spatial arrangements at the aging face, so intensity gradients were used to detect probable line location, then probability model was used to constrain properties of the line segment. In addition, Batool and Chellappa used the Reversible Jump Markov Chain Monte Carlo (RJMCMC) algorithm to MPP sampling that used to localize the wrinkles. The model could allow the incorporation of wrinkles, also the detected wrinkles spatial curve patterns could be incorporated in biometric applications. Finally, the presented detection algorithm could enable the use of a large set of images with baseline wrinkles for that purpose [xxxiii]. This algorithm has the ability to detect clear and deep wrinkles, but it failed to detect other wrinkles’ types. It also focused on forehead and horizontal wrinkles, it neither detect other facial regions nor detect vertical wrinkles.

In 2014, Batool and Chellappa developed a new algorithm [xxvii] to detect facial wrinkles and imperfections that could be used for facial retouching applications. The algorithm was used to detect forehead wrinkles. Two types of features from the forehead area were conducted using texture orientation and Gabor filter. Firstly they used Gabor Filter to highlight the intensity gradients in any directions, then orientation field highlighted the discontinuities in the normal flow of skin texture. After that they merged highlighted features using Gaussian Mixture Models (GMM) and Markov random field representation. The result of this algorithm is better than the previous algorithm developed by same researchers, but it has limitation in detecting complex wrinkles, moreover, the algorithm did not address false positive value.

A year later, Batool and Chellappa developed another wrinkles detection algorithm, which they called it as fast wrinkles detection algorithm [xli]. The algorithm used Gabor Filter Bank to extract the features of images, it also used image morphology to incorporate geometric constraints that used to localize curvilinear shapes of wrinkles at image sites. To validate the algorithm, researchers used two types of datasets; low and high resolution (some images from FGNet and the other 125 high resolution images of famous persons downloaded from the Internet). The experiments showed that the proposed algorithm is faster and gives better results for wrinkles localization in addition to decrease the false positive detection compared to their previous algorithm in [xxxiii].

This paper tried to shed light on the most important and state-of-the-art automatic wrinkles detection related to the last ten years. Wrinkle detection went through many stages, started at manual wrinkle detection till it reached automatic wrinkle detection. The enhancement within algorithms
used to automatic wrinkle detection accompanied all automatic wrinkle detection stages led to great algorithms like HHF [ix] and HLT [iv], but it needs more improvement, all the above algorithms focused to detect horizontal lines in forehead region, while the wrinkles can be appeared as vertical lines on other facial regions.

Omaima et al. [xlv] conducted a study to investigate the effects of smoking on whole facial wrinkles using social habit face dataset [xlvi]. Modified HHF was proposed to detect the facial wrinkles; this algorithm is used to detect horizontal and vertical wrinkles. The face was split into 10 regions [xlvii], then the algorithm was applied to them separately. The result showed that the density of wrinkles for smokers in the regions around the mouth was significantly higher than the non-smokers, at p-value of 0.05. This algorithm considered as the first method that tried to detect vertical line, but it did not validated using state-of-the-art dataset. So, more improvement is needed.

The transient wrinkles, like expression wrinkles did not have sufficient study, due to the nature of wrinkles’ types (shape complexity and diversity), so, most studies focused on permanent wrinkles detection like age wrinkles which have usually linear shape. In 2017, Xie et al. [xlviii] proposed a novel transient wrinkle detection algorithm and its application for expression synthesis. In this algorithm, edge pair matching and active appearance model (AAM) were used for wrinkle structure location, in addition to support vector machine (SVM) which used for wrinkle classification. Compared to state-of-the-arts algorithm, the algorithm yield complete and accurate wrinkle centers, also the expression synthesized by the improved wrinkle mapping was much more realistic.

All studies above used one of different approaches that are used for wrinkles detection. The popular one is snakebased approach, this approach uses active contour map to localize and initialize the wrinkles as mentioned in [x] [xxxiii]. Also filter-based is one of the approaches that are used to detect the wrinkles as mentioned in [xlii] [iv] [ix], this approach contributes in developing new algorithms which have good affect on wrinkles detection field.

Fig.1. Number of publications for automatic wrinkles detection algorithms over the past 10 years.

VII. Conclusion and Future Work

A survey on the manual and automatic wrinkles detection techniques was presented in this paper including state-of-the-art methods that recorded good results for automatic wrinkles detection. Although there were some methods achieved very good results like Gabor [xxvii], HHF [ix] and HLT [iv], but these research field need more enhancement. Existing wrinkles detection algorithm are focusing on the forehead wrinkles detection [xli] [ix], however, the wrinkles are important to many applications like age estimation and soft biometric. While there are methods just focus on detecting the horizontal lines, it is important to consider the vertical lines in some facial regions. So, it is better to detect wrinkles (vertical and horizontal) for all face rather than just forehead wrinkles. Another factor that can affect on the performance of detection is the dataset. Existing methods work very well with faces that contain medium and coarse type of wrinkles, but fine lines still caused a problem. Moreover, the methods of machine learning and deep learning are not widely used in this type of algorithm, except [xlviii] where they used machine learning. This research direction may add some progress in the automatic wrinkles detection algorithm, some future direction for automatic wrinkles detection methods are as follow:

- Automatic wrinkles detection algorithm for all facial wrinkles.
- Horizontal and vertical facial wrinkles detection.
- Collect dataset which consists of faces from diverse demographic.
- Improve existing methods to address fine line detection.
- More studies on deep learning and machine learning in wrinkles detection.
TABLE II: A Summary of Automatic Wrinkles Detection Algorithms.

<table>
<thead>
<tr>
<th>Year</th>
<th>Author</th>
<th>Dataset</th>
<th>Area of Detection</th>
<th>Accuracy and Metrics</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>Batoool and Chellappa [XXIII]</td>
<td>images from internet</td>
<td>Forehead Wrinkles</td>
<td>Quantitative evaluation</td>
</tr>
<tr>
<td>2013</td>
<td>Cula et al. [XLII]</td>
<td>100 clinically pathological images</td>
<td>Forehead Wrinkles</td>
<td>Quantitative evaluation</td>
</tr>
<tr>
<td>2014</td>
<td>Batoool and Chellappa [XXVIII]</td>
<td>images from internet</td>
<td>Forehead Wrinkles</td>
<td>Quantitative evaluation</td>
</tr>
<tr>
<td>2015</td>
<td>Ng et al. [IX]</td>
<td>100 images from Bosphorus</td>
<td>Forehead Wrinkles</td>
<td>72.97% using JSI</td>
</tr>
<tr>
<td>2016</td>
<td>Batoool and Chellappa [XXVIII]</td>
<td>FG-Net images from internet</td>
<td>Forehead Wrinkles</td>
<td>Quantitative evaluation</td>
</tr>
<tr>
<td>2015</td>
<td>Ng et al. [IV]</td>
<td>100 images from Bosphorus</td>
<td>Forehead Wrinkles</td>
<td>84.00% using JSI</td>
</tr>
<tr>
<td>2017</td>
<td>Ohashi et al. [XV]</td>
<td>Social habits database</td>
<td>Whole Face</td>
<td>P-value of 0.05</td>
</tr>
<tr>
<td>2017</td>
<td>Xie et al. [XLVIII]</td>
<td>CR+ database</td>
<td>Different Facial Regions</td>
<td>JSI with 0.52%</td>
</tr>
<tr>
<td>2018</td>
<td>Ng et al. [XLI]</td>
<td>Morph, FERET, FG-NET</td>
<td>Whole Face</td>
<td>MORPH 3.68, MAE FERET 3.02, FG-NET 3.66</td>
</tr>
</tbody>
</table>

References


iv. C.-C. Ng, M. Yap, N. Costen, and B. Li, “Wrinkle detection using hessian line tracking,” 2015


