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Facial Wrinkles Detection Algorisms: A Review

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Abstract: Aging is a natural phenomenon that affects the human body, where the most important features that occursaccording to the progress of age are facial wrinkles, which are thefocus of this paper. Wrinkles detection plays an important rolein facial analysis. Some wrinkles detection algorithms achieved good results like Gabor Filter, Hybrid Hessian Filter and HessianLine Tracking, but further enhancements needed in this researcharea. 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 automaticwrinkles detection techniques will be presented in this paper.Furthermore, we present four state-of-the-art datasets that canbe used for wrinkles detection evaluation. We discuss the performancemetrics for wrinkles detection algorithm, and concludethe 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) radiationare affecting the face features. These factors contributeto change of facial skin, and the overall face shape will beaffected by these changes in addition to features change ofthe face: folds, wrinkles, and lines will be appear and becomemore obvious with age i].

Physiologically, many facial features are changes as peoplegetting older, where facial wrinkle is one of these features. Itappears and become more obvious with age. These wrinkles are changed based on the skin nature and muscle contraction[ii]. Wrinkles can be defined as creases or small furrow infacial skin that caused by expressions or age. Ekman et al.[iii] described wrinkles as a line with depth and sometimesthe 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 wrinkle and it willbe deepen with certain actions. In 2D images, the wrinklesare affecting the skin; it creates deep creases and sometimescreates curvature in the skin surrounding, this curvature willaffect the overall facial skin [iv]. The wrinkles characteristicscan be described using two major factors: one of them used todefine the location of wrinkles curve lines, this called furrow or macro, and the other one is bulge, which is used to givecurved surface shape [v].

Wrinkles where it considered as temporary wrinkles, but may become permanent with time. The latter is permanent wrinkleswhich are appearing with age. Furthermore, as mentioned in[vi], the wrinkles can be divided into four types according towrinkles pathogenesis and histological conditions. First typeis atrophic; these types of wrinkles appear as parallel lines andthey disappear when skin is put under transversal tension.Second type is elastotic; this type is appearing when the skinis exposing to sun and it considered permanent. Third type isexpressional, as mentioned above, it is temporary wrinkles, butit may become permanent lines. Fourth type is gravitational; itresulted from gravitational forces inducing folding and saggingof skin which has lost its turgidity.

Human eye can detect wrinkles easily, but it is a verydifficult task to detect wrinkles automatically using imageprocessing techniques. This is due to the wrinkles shape isvarying according to ethnic group, gender, age, and personallife style. Also it depends on the image quality that wasaffected by image acquisition environment [vii].

Many different approaches in detecting the features changes on the face exist, including detection of facial wrinkles. Earlierwork in wrinkles detection was proposed by Lod´en et al. [viii],they used silicone to produce the facial wrinkles by makingreplica using this silicone and made the measurements dependson it. But these old studies were not efficient enough, becauseit is very difficult to get silicone replicas same as the actualskin morphology. In 2014, Ng et al. [ix] proposed HybridHessian Filter (HHF) to detect and quantify the facial wrinkles automatically; their algorithm recorded very good results indetecting wrinkles.

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

This paper is organized into the following sections: Section2 presents the application of wrinkles detection algorithm.Section 3 describes four state-of-the-art datasets that can beused for facial application. Section 4 explains the performancemeasurement 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 bepresented in Section7.

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 application, like age estimation [x] [xii], and synthesis [xiii], face modeling [xiv], facial expression recognition [xv], and it can be used as soft biometric [xvi].

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 [xiii].

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 [xxii] [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 Batool 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 105subjects; 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.

Datasets	*Number of Subject*	*Number of Images*	*Age Range*
Bosphorus	4666	105	25 - 35
FG-NET	1002	82	0 - 69
FERET	2366	994	10 – 70
MORPH	55,134	13,000	16 - 77

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 [xxxiii]. JSI is the most commonly used method in medical imaging analysis, this techniques originally introduced by Paul Jaccard [xxxiv], 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 [xxxiii]; 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.

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

- 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).

$$r_{false} = \frac{\Sigma_{n_D} L_{false}}{\mathrm{v(s)} - \Sigma_{n_w} L_{original}}$$

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

$$r_{miss} = \frac{\Sigma_{n_D} L_{false}}{\Sigma_{n_w} (L_{overlap} + L_{miss})}$$

Wherer_{miss} = 1 - r_{detect} andn_w, $n_D$are thetotal number of hand drawn and detected wrinklesrespectively.

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] [xxxv] [xxxvi]. 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 isusing three dimensional optical profilometers based on digital morphology as mentioned in [xxxvii][xxxviii], the limitation of thisapproach 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. [xl] 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 experimentII, the participant compared between each pair of faces todetermine the similarities of features that had more effects onthe face. The results showed that the wrinkle’s number hadmore influence on age of the face than the wrinkle type.

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

VI. Automatic Wrinkles Detection

The great improvement in computer vision motivates researchers to spot light on multiple algorithms like automaticwrinkles detection algorithm that considered as important stepin 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 onhuman age based on three age groups; which are babies,young adults, and senior adults. Firstly, they detected theprimary features of each face: like eyes, nose, mouth, chin,and virtual top of the head, the output was distinguished thebaby from others. Secondly, the facial wrinkles was detectedusing wrinkles geography map, then the output distinguishedthe seniors adults from younger adults categories. On the otherhand, Choi et al. [x] proposed wrinkle representation schemeto estimate age of the skin by construct skeleton consistedof most features related to the wrinkles using watershedalgorithm to represent the wrinkles on skin of the image.

The above mentioned studies tried to identify the effectof facial wrinkles on human age, but there are researcherjust focused on developing algorithms to detect the wrinklesautomatically. Table 2 and Figure 1 depict the development ofautomatic wrinkles detection methods over the past 10 years in chronological order. Cula et al. [xlii] developed automaticwrinkles detection algorithm, it was based on orientationestimation and the frequency of elongated spatial features.They used a set of facial images that was clinically validatedto detect the wrinkles that appear on the forehead, the wrinklescale for these images was varying from 0 (no wrinkle) to 11(most severe wrinkles). The algorithm was tested using twocases: First they combined the wrinkles depth information withthe wrinkles length information, and second they separated thewrinkles length information from the wrinkles depth information.The algorithm performed better in the first case. Thisalgorithm considered as one of the earliest automatic wrinklesdetection algorithms in 2D images, but it has some

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limitationsin wrinkles localization, and in distinguishing wrinkle fromimage noise like hair, scars or illumination.

After Cula et al. [xlii], other researchers tried to improvethe quality of automatic wrinkles detection methods. Ng etal. [ix] developed a novel method for automatic wrinklesdetection, it called Hybrid Hessian Filter (HHF). HHF isan algorithm for automatic wrinkles detection in 2D facialimages. The algorithm based on Hessian matrix and directionalgradient which is used to detect the facial wrinkles by computethis matrix to all pixels for each image, the Hessian Matrixmaximum eigenvalues indicates whether or not the point isa part of a ridge regardless this ridge's orientation. Eachpoint (x; y) fields second derivative component measureseigenvalues (independent vector), the more small eigenvalues,the more fields corresponding eigen-direction change a littleand vice versa. HHF used 100 random selected images fromBosphorus dataset [xxx], from these images, researcher usedforehead area, so they cropped the images manually withrectangle selector. The algorithm was showed better resultcompared to other methods such as Cula's method [xlii], itconsidered outperformed state of the art methods with averageJSI of 75.67%. According to this result, HHF considered as astrong wrinkles detection algorithm compared to other state-of-the-art methods, it had a good result regarding wrinkleslocalization in addition to increasing the correctly detectedwrinkles' number. HHF recorded very good result for foreheadespecially medium and coarse wrinkles, but, more effort isneeded to improve this algorithm, it neither detect wrinkleson other facial regions, nor detect vertical lines.

As an extension to HHF, Ng et al. [iv] developed HessianLine Tracking (HLT), tried to overcome the problemsof previous automatic wrinkles detection methods. HLT isan algorithm for automatic wrinkles detection in 2D facialimages, it composed of hessian seeding and directional linetracking. HLT executed in many steps; firstly HHF was usedto extract the seeds and then the optimum pixels for startingpoint determined. Line tracking was used to determine eachpixel belongs to wrinkle line. Then post processing usingmedian and directional filter in addition to area thresholldingwas applied to remove the noise (outlier). The algorithm wasvalidated using 100 manually cropped forehead faces fromBosphorus dataset [xxx]. when HLT compared to benchmarkalgorithms like Cula's algorithm [xlii], Frangi Filter (FRF)[xliii] and HHF [ix] it performed better result with accuracyof 84.00%. HLT considered a strong detector of foreheadwrinkles in 2D images, add to that, the algorithm has abilityto explore the curve and valley pattern in order to wrinkleconnectivity, but it needs more enhancement to detect otherfacial wrinkles and vertical lines.

More recently, Ng et al. [xliv] have proposed to use wrinklesas complementary features for face age estimation. Theyproposed two new methods in this study, Multi-scale WrinklePatterns (MWP) used as a feature representation for facialwrinkles and Hybrid Ageing Patterns (HAP) used as a newfeature representation for face age estimation. HLT [iv] wasused as wrinkles detector in MWP after tested against state-of-the-art wrinkles detection methods (HHF [ix],Cula's method[xlii], and Batool's method [xli]) 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], andMorph [xxxii]) were used to assess the performance of HAP, itrecorded 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 facialwrinkles detection [xxxiii][xxvii][xli]. In 2012, they proposeda novel modeling technique for wrinkles, based on spatialmarked point processes (MPP). They considered the wrinklesas sequences segments of line that appear as stochastic spatialarrangements at the aging face, so intensity gradients wereused to detect probable line location, then probability modelwas used to constrain properties of the line segment. Inaddition, Batool and Chellappa used the Reversible JumpMarkov Chain Monte Carlo (RJMCMC) algorithm to MPPsampling that used to localize the wrinkles. The model couldallow the incorporation of wrinkles, also the detected wrinklesas spatial curve patterns could be incorporated in biometricapplications. Finally, the presented detection algorithm couldenable the use of a large set of images with baseline wrinklesfor that purpose [xxxiii]. This algorithm has the ability to detectclear and deep wrinkles, but it failed to detect other wrinkles'types. It also focused on forehead and horizontal wrinkles, it neither detect other facial region, nor detect vertical wrinkles.

In 2014, Batool and Chellappa developed a new algorithm[xxvii] to detect facial wrinkles and imperfections that couldbe used for facial retouching applications. The algorithm wasused to detect forehead wrinkles. Two types of features fromthe forehead area were conducted using texture orientationand Gabor filter. Firstly they used Gabor Filter to highlightthe intensity gradients in any directions, then orientation fieldhighlighted the discontinuities in the normal flow of skintexture. After that they merged highlighted features usingGaussian Mixture Models (GMM) and Markov random fieldrepresentation. The result of this algorithm is better thanthe previous algorithm developed by same researchers, but ithas limitation in detecting complex wrinkles, moreover, thealgorithm did not address false positive value.

A year later, Batool and Chellappa developed anotherwrinkles detection algorithm, which they called it as fastwrinkles detection algorithm [xli]. The algorithm used GaborFilter Bank to extract the features of images, it also usedimage morphology to incorporate geometric constraints thatused to localize curvilinear shapes of wrinkles at image sites.To validate the algorithm, researchers used two types ofdatasets; low and high resolution (some images from FG-Netand the other 125 high resolution images of famous personsdownloaded from the Internet). The experiments showed that the proposed algorithm is faster and gives better results forwrinkles 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 andstate-of-the-art automatic wrinkles detection related to thelast ten years. Wrinkle detection went through many stages,started at manual wrinkle detection till it reached automaticwrinkle detection. The enhancement within algorithms usedto automatic wrinkle detection accompanied all automaticwrinkle detection stages led to great algorithms like HHF [ix]and HLT [iv], but it needs more improvement, all the abovealgorithm focused to detect horizontal lines in forehead region,while the wrinkles can be appeared as vertical lines on otherfacial 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 splitted 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-0value 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.

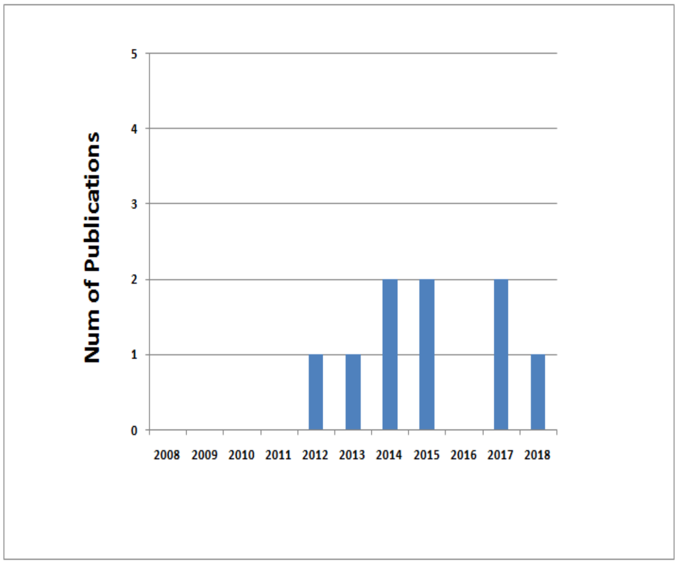

Fig.1. Number of publications for automatic wrinkles detection algorithms over the past 10 years.

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.

Year	Author	Dataset	Area of Detection	Accuracy and Metrics
2012	Batool and Chellappa[XXXIII]	images from internet	Forehead Wrinkles	Quantitative evaluation
2013	Cula et al. [XLII]	100 clinically gradedfacial images	Forehead Wrinkles	Quantitative evaluation
2014	Batool and Chellappa [XXVII]	images from internet	Forehead Wrinkles	Quantitative evaluation
2014	Ng et al. [IX]	100 images from Bosphorus	Forehead Wrinkles	72.67% using JSI
2015	Batool and Chellappa [XXVII]	FG-Net, Images from internet	Forehead Wrinkles	Quantitative evaluation
2015	Ng et al. [IV]	100 images from Bosphorus	Forehead Wrinkles	84.00% using JSI
2017	Omaima et al. [XLV]	Social habits dataset	Whole Face	P-value of 0.05
2017	Xie et al. [XLVIII]	CK+ database	Different Facial Regions	JSI with 0.52%
2018	Ng et al. [XLIV]	Morph, FERET, FG-NET	Whole Face	MORPH 3.68 MAE, FERET 3.02, FG-NET 5.66

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