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A Survey on Facial Feature Points Detection Techniques and Approaches

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***Abstract*—** Automatic detection of facial feature points plays an important role in applications such as facial feature tracking, human-machine interaction and face recognition. The majority of facial feature points detection methods using two-dimensional or three-dimensional data are covered in existing survey papers. In this article chosen approaches to the facial features detection have been gathered and described. This overview focuses on the class of researches exploiting facial feature points detection to represent facial surface for two-dimensional or three-dimensional face. In the conclusion, we discusses advantages and disadvantages of the presented algorithms.

***Keywords*—**Facial feature points, face recognition, facial feature tracking, two-dimensional data, three-dimensional data.

I. Introduction

In publications, facial feature points are also referred to as facial points, ducial facial points, or facial landmarks [1]-[3]. Facial feature points are visible marks in facial images or points that constitutes an interesting parts of images, such as the eye centers, the nose tip, the mouth corners, and other salient facial points. They are often used as a reference or for measurement. Some examples of facial feature points are illustrated in Fig. 1.

The localization of stable facial points such as the inner corners of the eyes and the inner corners of the nostrils is also usually used to register each frame of an input image sequence with the first frame of it. In turn, the robustness of the facial feature point detection algorithm highly affects the overall system performance. Facial feature point detection has been widely employed in facial image processing, such as facial feature segmentation [4], face recognition [2], face animation [5], face alignment and tracking [6], lip reading [7], [8], head motion detection [9], and facial expression recognition [10]. These studies have also been applied to various computer vision systems and human-machine interfaces [11]. Detection of facial feature points is often the first step in computer vision applications such as face identification, facial expression recognition, face tracking and lip reading. Currently, however, this step is usually carried out by manually labeling the required set of points.

Recently, extensive work has focused on automatic feature localization from 2D images of the face contains facial texture and color information. Previous methods for facial feature point detection of 2D images could be classified in two categories: Texture-based and shape-based methods [25]. Texture-based methods model local texture around a given feature point. Shape-based methods regard all facial feature points as a shape.

Typical texture-based methods include gray-value, eye-configuration- and neural-network-based eye-feature detection [12], log Gabor wavelet based facial point detection [13], and two-stage facial point detection using a hierarchy of Gabor wavelet networks [14]. Typical shape-based methods include active appearance model based facial feature detectors [15], [16]. The active appearance model (AAM) by Cootes et al. [20] is one of the most effective facial landmark detection algorithms on 2D images. An iterative search algorithm seeks the best location for each feature using a texture model describing that features surrounding. These feature locations are then fine-tuned using the spatial distribution of feature points encoded by a shape model. In a later work, Cristinacce et al. [21] improved the AAM algorithm and showed that their new shape optimized search (SOS) algorithm outperforms the AAM. A number of approaches combining texture- and shape-based methods have been proposed as well. Wiskott et al. [17] used Gabor jet detectors and modeled the distribution of facial features with a graph structure. Cristinacce and Cootes used Haar feature based AdaBoost classifier combined with the statistical shape models [18]. Chen et al. proposed a method that applies a boosting algorithm to determine facial feature point candidates for each pixel in an input image and then uses a shape model as a filter to select the most possible position of feature points [19].

There have been very few techniques proposed in the literature that use 3D facial information for fiducial detection. The existing ones are mainly based on mean and Gaussian curvatures extracted from range images. Curvature features are very sensitive to 3D acquisition noise; therefore, they require extensive preprocessing. Recent studies [22] show that these techniques suffer from a large number of false positives and thus result in low accuracies. In 2005, X. Lu and A. K. Jain propose a multimodal scheme to integrate 3D (range) and 2D (intensity) information provided from a facial scan to extract the feature points [23]. In 2010 M. yu use a 3D extension of the Constrained Local Model (CLM) algorithm for facial feature detection and tracking [24].

The rest of this paper is organized as follows: In Section II, we represent the existing methods, in Section III, we present the extraction of facial curves and surface reconstruction by iso-geodesic curves, in Section IV, we represent a

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mathematical approach of facial surfaces and Riemannian analysis of facial curves and in Section V, we represent simulation results of presented method.

II. Facial Feature Points Detection Methods for 2D Images

A. Gabor Feature Based Boosted Classifiers

In 2005, Danijela Vukadinovic and Maja Pantic [25] presented a method for fully automatic detection of 20 facial feature points in images of expressionless faces using Gabor feature based boosted classifiers. The method adopts fast and robust face detection algorithm, which represents an adapted version of the original Viola-Jones face detector. The detected face region is then divided into 20 relevant regions of interest, each of which is examined further to predict the location of the facial feature points. The proposed facial feature point detection method uses individual feature patch templates to detect points in the relevant region of interest. These feature models are GentleBoost templates built from both gray level intensities and Gabor wavelet features. When tested on the Cohn-Kanade database, the method has achieved average recognition rates of 93%. Fig. 2 shows this 20 facial feature points detection such as: Outer corner of the left eye, outer corner of the right eye, inner corner of the left eye, inner corner of the right eye, bottom of the left eye, bottom of the right eye, top of the left eye, top of the right eye, inner corner of the left eyebrow, inner corner of the right eyebrow, outer corner of the left eyebrow, outer corner of the right eyebrow, left nose corner, right nose corner, top of the nose, left mouth corner, right mouth corner, mouth top, mouth bottom and chin.

Fig. 1 Example of 20 facial feature points detection [25]

The method consists of 4 steps [25]: 1- Face Detection using Haar feature based GentleBoost classifier. 2- Region of Interest (ROI) Detection. 3- Feature Extraction based on Gabor filtering. 4- Feature Classification using Gentle Boost classifier. The facial feature detection method was trained and tested on the Cohn-Kanade database, which consists of approximately 2000 gray-scale image sequences in nearly frontal view from over 200 subjects, male and female, 18-50 years old. The detection rates for each point are shown in Table I. The method has achieved average recognition rates of 93% [25].

TABLE I
Facial Feature Point Detection Results for 300 Samples from the Cohn-Kanade Database [25]

Detected Point	Detect. Rate
Outer corner of the left eye	0.92
Outer corner of the right eye	0.96
Inner corner of the left eye	0.96
Inner corner of the right eye	0.99
Bottom of the left eye	0.95
Bottom of the right eye	0.99
Top of the left eye	0.91
Top of the right eye	0.83
Inner corner of the left eyebrow	0.96
Inner corner of the right eyebrow	0.95
Outer corner of the left eyebrow	0.96
Outer corner of the right eyebrow	0.90
Left nose corner	0.98
Right nose corner	0.97
Left mouth corner	0.97
Right mouth corner	0.91
Mouth top	0.93
Mouth bottom	0.80
Chin	0.90
AVERAGE	0.93

B. Face Segmentation and Localizing the Face Components

In 2008, Bevilacqua et al. presented an algorithm which detects automatically the feature points in a face image. Starting from a frontal face image with a plain background, they have affected an image segmentation to detect the different facial components (eyebrow, eyes, nose, mouth and chin). After this, they have searched for the feature points of each face component. The algorithm has been tested on 320 face images taken from the Stirling University Face Database [26].

Fig. 2 Examples of 18 facial feature points detected [26]

The proposed algorithm can be divided into two parts. First of all, they have a face segmentation in which we localize the various face components (eyebrows, eyes, mouth, nose and chin). After this, in each component, they detect 18 features points: The two pupils, the four eye corners, the four eyebrow corners, the two nostrils, the nose tip, the two mouth corners, the upper and lower lip extremity and the tip of chin. Fig. 2 gives examples of 18 facial feature points detected using this method.

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The automatic facial feature points detection algorithm has been tested on 320 images taken from the Stirling University Face Database. The errors have been calculated as the distance in pixel between the manually located points and the ones automatically obtained with the developed algorithm. Table II presents the errors found [26].

TABLE II
FACIAL FEATURE POINT DETECTION ERRORS FOR 320 IMAGES TAKEN FROM THE STIRLING UNIVERSITY FACE DATABASE [26]

Feature point	Errors. Rate (%)
Right eye pupil	2.07
Left eye pupil	2.60
Right eye outer corner	3.52
Right eye inner corner	4.07
Left eye outer corner	4.58
Left eye inner corner	4.14
Right eyebrow outer corner	13.02
Right eyebrow inner corner	12.08
Left eyebrow outer corner	10.29
Left eyebrow inner corner	14.75
Left nostril	5.50
Right nostril	4.67
Nose tip	6.72
Left mouth corner	4.31
Right mouth corner	4.39
Top mouth	5.90
Bottom mouth	5.45
Tip of chin	7.23
AVERAGE	6.405

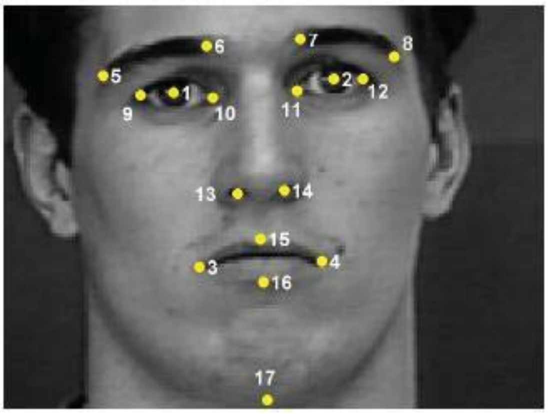

Fig. 3 Example of three Euclidean distances between facial feature points [27]

C. HOGs and Geometric Prior Models

In 2011, M. R. Quiones et al. [27] presented a simple method to detect facial salient points in the face. It is based on a prior Point Distribution Model and a robust object descriptor. The model learns the distribution of the points from the training data, as well as the amount of variation in location each point exhibits. Using this model, they reduce the search areas to look for each point. In addition, we also exploit the global consistency of the points constellation, increasing the detection accuracy. The method was tested on with 570 images of the Cohn Kanade and 350 images the BioID databases. The algorithm detects 17 facial features points, Fig. 3 shows the 17 points extracted using this method. This system intends to view the detection problem as a classification one. It learns the model for each fiducial point using the HOG algorithm to compute the descriptor over a local neighborhood and trains a GentleBoost classifier. Subsequently, it learns the distribution of points in the reference frame of the face bounding box from the training set. During test it uses as a basis the face localization and a pair of reference points. This information is used to adjust the model of the spatial location and center the search areas, reducing the computational cost by limiting the amount of points to test. The method was evaluated with 570 images of the Cohn Kanade and 350 images the BioID databases [27]. The results shown for the performance are given in Table III.

TABLE III
PERFORMANCE RESULTS FOR THE SYSTEM ON THE COHN KANADE AND BIOID DATASETS PER POINT [27]

Feature point	Detection Rate (%)	Errors Rate (%)	Detection Rate (%)	Errors Rate (%)
1	99.57	2.72	100.00	1.84
2	96.98	3.24	99.82	2.08
3	89.66	6.70	98.07	3.12
4	94.40	4.80	98.77	3.08
5	73.71	6.92	83.68	5.92
6	77.59	6.63	88.60	4.77
7	76.29	6.50	92.63	4.31
8	81.47	6.09	88.07	5.11
9	99.57	3.63	99.65	3.28
10	98.71	3.33	100.00	2.55
11	99.57	3.24	99.82	2.91
12	97.41	3.69	100.00	2.80
13	96.55	4.04	99.82	2.66
14	98.71	3.53	100.00	2.57
15	98.71	3.89	99.12	2.88
16	73.28	9.70	93.16	4.63
17	54.74	16.52	68.95	8.26
AVERAGE	88,642	11,358	94,715	5,285

D. Anthropometric Face Model

In 2008, Sohail and Bhattacharya [28] presented an automatic technique for detecting the 18-most important facial feature points using a statistically developed anthropometric face model. Most of the important facial feature points are located just about the area of mouth, nose, eyes and eyebrows. After carefully observing the structural symmetry of human face and performing necessary anthropometric measurements, they have been able to build a model that can be used in isolating the above mentioned facial feature regions. In the model, distance between the two eye centers serves as the principal parameter of measurement for locating the centers of other facial feature regions. Hence, this method works by detecting the two eye centers in every possible situation of eyes and isolating each of the facial feature regions using the model. Combinations of different image processing techniques are then applied within the localized regions for detecting the 18-most important facial feature points. Experimental result shows that the developed system can detect the 18-feature points successfully in 90.44% cases when applied over the test databases. This method was evaluated on three publicly available face image databases namely, Caltech Face Database, BioID Face Database, and Japanese Female Facial Expression

Database. The results shown for the performance are given in Table IV.

TABLE IV
DETECTION ACCURACY (IN PERCENT) OF THE AUTOMATIC FACIAL FEATURE POINT DETECTOR [28]

Feature point	**Caltech Face Database (%)**	**BioID Face Database (%)**	**JAFFE Database (%)**	**Average Accuracy (%)**
Right Eyebrow Inner Corner	95.41	94.16	98.57	96.05
Right Eyebrow Outer Corner	87.36	90.42	92.17	89.98
Left Eyebrow Inner Corner	96.20	93.52	96.38	95.37
Left Eyebrow Outer Corner	88.40	86.26	90.35	88.34
Right Eye Inner Corner	93.12	90.83	94.70	92.88
Right Eye Outer Corner	85.34	87.92	89.62	87.63
Mid Point of Right Upper Eyelid	84.49	86.71	88.4	86.53
Mid Point of Right Lower Eyelid	83.60	85.38	86.73	85.24
Left Eye Inner Corner	95.11	92.64	92.83	93.53
Left Eye Outer Corner	86.69	90.76	91.46	89.64
Mid Point of Left Upper Eyelid	85.77	88.26	89.61	87.88
Mid Point of Left Lower Eyelid	84.22	87.69	88.98	86.96
Right Nostril	97.23	93.19	98.34	96.25
Left Nostril	96.95	91.88	97.21	95.35
Right Mouth Corner	92.79	87.40	95.32	91.84
Left Mouth Corner	94.10	92.45	97.89	94.81
Mid Point of Upper Lip	85.73	83.91	91.20	86.95
Mid Point of Lower Lip	79.31	82.33	86.28	82.64
AVERAGE	89,545	89,206	92,558	90,437

E. SUSAN Operator

In 2001, Quiones et al. [29] presented a simple method to detect facial salient points in the face. It is based on a prior Point Distribution Model and a robust object descriptor. The model learns the distribution of the points from the training data, as well as the amount of variation in location each point exhibits. Using this model, they reduced the search areas to look for each point. In addition, we also exploit the global consistency of the points constellation, increasing the detection accuracy. The method was tested on with 570 images of the Cohn Kanade and 350 images the BioID databases. The algorithm detected 17 facial features points, Fig. 3 shows the 17 points extracted using this method. This method consists of several steps [29]: 1- the location of the whole face; 2- the detection of facial features; and 3- the determination of the feature points. The authors used a perceptually uniform chromatic system to represent color information for increasing the robustness of the system. The regions of human face and its features are detected from the input image by applying the integral projection method, which analyses both the color information (the skin color and the hair color) and the edge information (strength and orientation). The threshold value is determined dynamically by calculating the average value of the integral projection applied to each search region. By using the information about the color and the edge, and the dynamic threshold, this system becomes robust to the change of the illumination condition and the complex background of the input images. In each region containing facial feature, the SUSAN corner detector is applied to detect the facial feature points. This automatic and robust system detects the facial feature points containing the both sides of the eyebrows, the eyes, the nose and the mouth. Fig. 4 shows an example result of detected of facial feature points. This method was evaluated on the Tokyo University Harashima Lab.s face database with complex background [29]. The accuracy of the extraction result about each the facial feature point about is summarized in Table V.

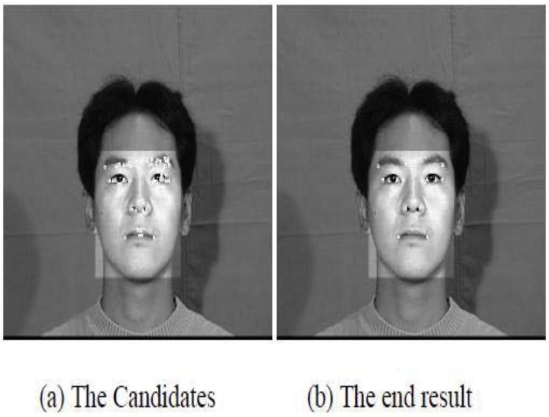

Fig. 4 The extracted facial feature points [29]

TABLE V
EXTRACTION PRECISION [29]

Region of face organ	**Errors Rate (%)**
left eyebrow (left)	1.2
left eyebrow (right)	0.3
right eyebrow (left)	5.8
right eyebrow (right)	4.1
left eye (left)	6.7
left eye (right)	2.6
right eye (left)	1.5
right eye (right)	4.3
nose (left)	14.1
nose (right)	7.9
mouth (left)	0.2
mouth (right)	0.0
AVERAGE	4,058

III. FACIAL FEATURE POINTS DETECTION METHODS FOR 3D IMAGES

A. Gabor Wavelet

In 2008, Jahanbin et al. [30] proposed an algorithms for 2D and 3D facial landmarking. In this technique, the appearance of each feature point is encoded using a set of Gabor wavelet responses extracted at multiple orientations and spatial frequencies. A vector of Gabor coefficients, called a jet, is computed at each pixel in the search window on a fiducial and compared with a set of jets, called a bunch, collected from a set of training data on the same type of fiducial. The desired feature point is located at the pixel whose jet is the most similar to the training bunch. This is the first time that Gabor wavelet responses were used to detect facial landmarks from range images. The algorithm detects 11 facial features points, Fig. 5 shows the 11 points extracted using this method. This method was tested on 1146 pairs of range and portrait images and high detection accuracies are achieved using a small number of training images [30]. It is shown that co-localization using Gabor jets on range and portrait images resulted in better accuracy than using any single image modality. The obtained accuracies are competitive to that of other techniques in the literature whereas with $m_e \leq 0.1$, the success rates of this presented method are more than 99% for any fiducial using any combination of range or portrait modalities [30].

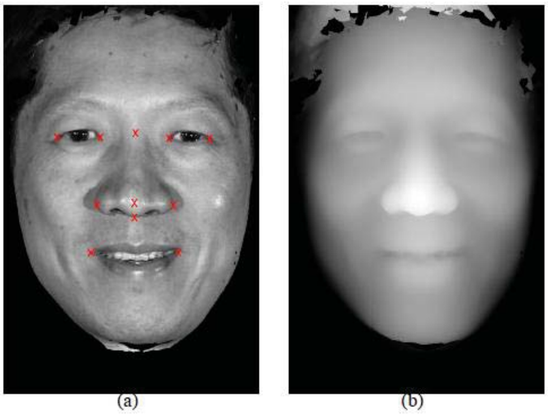

Fig. 5 Example of face images from the ADIR data set (a) A portrait image withmarked fiducial (b)The corresponding range image [30]

B. CLM

In 2010, Yu, and Tiddeman [31], [32] presented a 3D version of a 2D technique known as the CLM algorithm. This method uses a joint shape and texture appearance model which generates a set of region template detectors. By generating templates using the joint model and the parameter estimates, correlating the templates with the target image and optimising the shape parameters the template can be adapted to the target image [31].

The algorithm detects 25 facial features points, Fig. 6 shows the 25 points extracted using this method. The Bayesian CLM (BCLM) further extended this approach by framing it as a Bayesian inference problem. They further extended the BCLM approach to enable the use of 3D shape models. A 3D shape model is preferred on theoretical grounds and improved performance is confirmed via an empirical evaluation. The extension to 3D is developed by first introducing a full similarity transform to the (linearized) 2D CQF error function. The minimization of this error function gives a set of parameter updates that can be combined with the current estimates via a compositional approach. The adaptation of the algorithm to 3D then follows directly. The main contribution of this method is to develop and evaluate the extension of the BCLM framework to use 3D shape models. For training the 3D shape model, 3D surface models of 14 individuals were captured using a 3dMD stereoscopic system (www.3dmd.com). Each subject posed 14 expressions giving a total of 196 training models. Each model was landmarked in 3D in the same style as for the 2D images. The results show improved performance of 3DCLM [32].

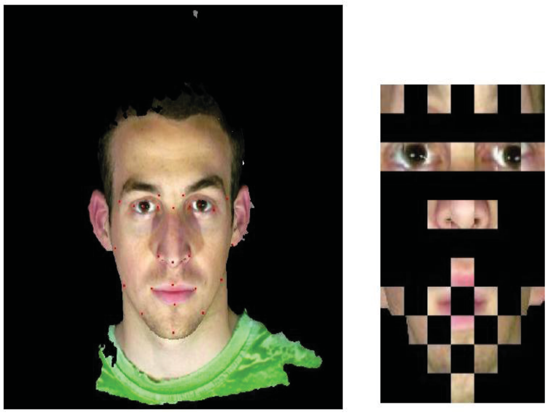

Fig. 6 Examples of 25 facial feature points detected [31]

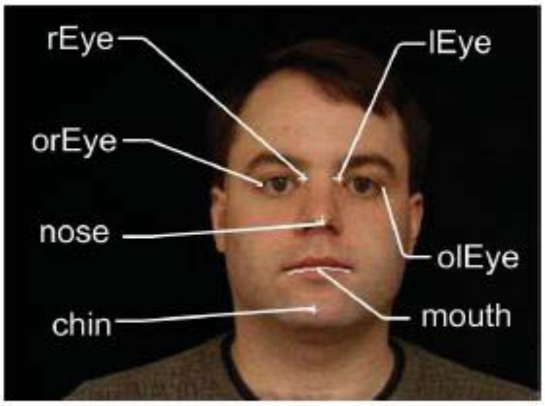

Fig. 7 Anchor point locations. rEye-Inside of the right eye; orEye-Outside of the right eye; lEye-Inside of the left eye; olEye-Outside of the left eye; nose-Nose tip; chin-chin tip; mouth-corners and middle of the mouth [33]

C. Frontal Anchor Point Detection (FAPD)

Colbry et al. [33] presented the methods to detect key anchor points in 3D face scanner data. These anchor points can be used to estimate the pose and then match the test image to a 3D face model. The FAPD algorithm starts by finding the top of the head. Any point near the top of the head should do because it only establishes the vertical location of the head. Once the top of the head is found, a bounding box for the location of the nose can be produced. The algorithm then uses other bounding boxes to localize the search for other anchor points. Each point is found using detection decisions based on local shape characteristics with parameters trained on sample scans. The algorithm detects 7 facial features points: rEye-Inside of the right eye; orEye-Outside of the right eye; lEye-Inside of the left eye; olEye-Outside of the left eye; nose-Nose tip; chin-chin tip; mouth-corners and middle of the mouth. Fig. 7 shows the 7 points extracted using this method. They present two algorithms for detecting face anchor points in the context of face verification; one for frontal images and one for arbitrary pose. They achieve 99% success in finding anchor points in frontal images and 86% success in scans with large variations in pose and changes in expression [33].

D. Multimodal Facial Feature Extraction

In 2005, Lu and Jain [34] used a multimodal scheme to integrate 3D (range) and 2D (intensity) information provided from a facial scan to extract the feature points. Given a face scan, the foreground is segmented from the background using the range map and the face area is detected using a real-time intensity-based algorithm. A robust nose tip locator is presented. A statistical 3D feature location model is applied after aligning the model with the nose tip. The shape index response derived from the range map and the cornerness response from the intensity map are combined to determine the positions of the corners of the eyes and the mouth. Real-world data are subject to sensor noise, resulting in spurious feature points. They introduced a local quality metric to automatically reject the scan whose sensor noise is above a certain threshold. The algorithm detects 7 facial features points, Fig. 8 shows the 7 points extracted using this method. As a result, a fully automatic multimodal face recognition system is developed. Both qualitative and quantitative evaluations are conducted for the feature extraction algorithm on a publicly available database, containing 946 facial scans of 267 subjects. This automatic feature extraction algorithm has been integrated in an automatic face recognition system. The identification performance on a database of 198 probe scans and 200 gallery subjects is close to that with manually labeled landmarks [34].

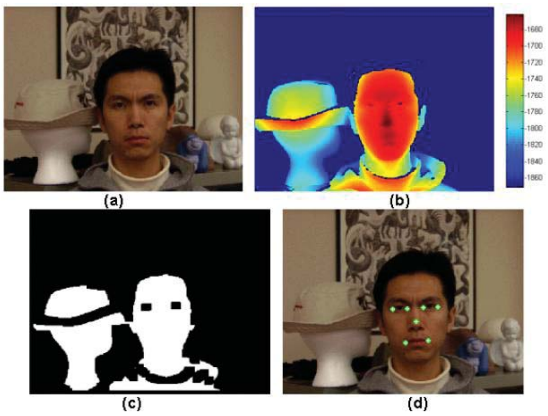

Fig. 8 Facial scan and feature points: (a) Intensity image. (b) Range image with the color map indicating the corresponding depth (z value). (c) Mask image provided by the sensor, indicating valid points (white). Notice the holes in the eye centers due to dark regions. (d) Feature points [34]

IV. Comparative Study

In this section, we present the performance of landmarking algorithms comparatively as tested on diverse face databases of 2D and 3D images. The comparative study of the different algorithms which are used for facial feature points detection have been shown in Figs. 9-11.

A. Comparative Study of 2D Images Methods

The comparative study was started by comparing of detection rate of each point for the different types of methods which have been employed in automatic facial feature point detection of 2D images like Gabor Feature Based Boosted Classifiers (GFBBC), Face Segmentation and Localize the Face Components (FS-LFC), HOGs and Geometric Prior Models (HOGGPM), Anthropometric Face Model (AFM) and SUSAN Operator (SUSAN-O). Fig. 9 presents the detection rate of each facial feature point using the different types of methods. There are many advantages and disadvantages for these algorithms. After summarization for these techniques, we can choose the better one which enables dealing with conditions that affect on face recognition like change in illumination, pose variation, change in expressions, Partial Occlusion and Noise etc.

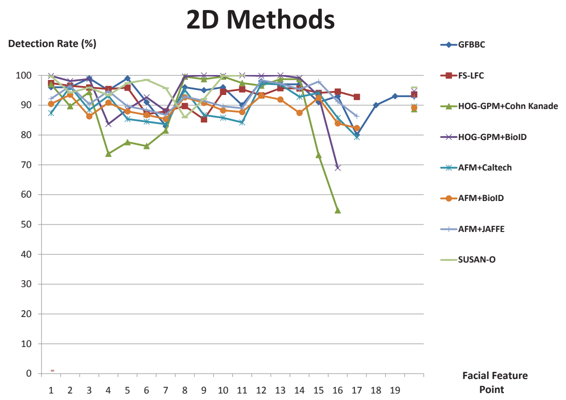

Fig. 9 Detection rate of each facial feature point per methods

Fig. 9 shows the detection rate of each facial feature point (1- Outer corner of the left eye, 2- Outer corner of the right eye, 3- Inner corner of the left eye, 4- Inner corner of the right eye, 5- Bottom of the left eye, 6- Bottom of the right eye, 7- Top of the left eye, 8- Top of the right eye, 9- Inner corner of the left eyebrow, 10- Inner corner of the right eyebrow, 11- Outer corner of the left eyebrow, 12- Outer corner of the right eyebrow, 13- Left nose corner, 14- Right nose corner, 15- Top of the nose, 16- Left mouth corner, 17- Right mouth corner, 18- Mouth top, 19- Mouth bottom and 20- Chin) using the detection methods (GFBBC, FS-LFC, HOG-GPM+Cohn Kanade, HOG-GPM+BioID, AFM+Caltech, AFM+BioID, AFM+JAFFE and SUSAN-O). This figure shows that each methods gives a good result for the detection of one point and the opposite for another. Therefore, this figure does not allow us to determine the best method among the methods used.

To determine the best method, we compared the average detection rates. Fig. 10 summarizes this comparative study and shows that the best method is SUSAN Operator (SUSAN-O) using Tokyo University Harashima Lab.'s face database with complex background with an average detection rate of $95,942\%$.

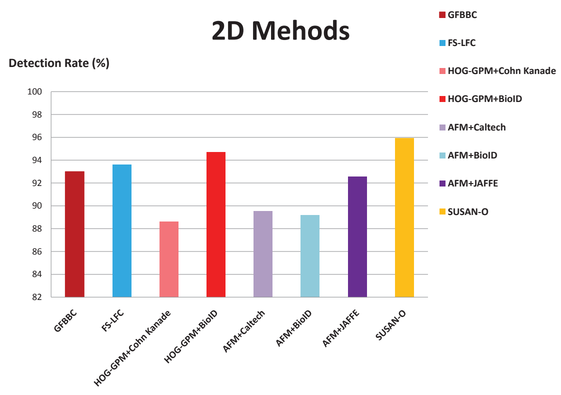

Fig. 10 Comparative study of average detection rate of 2D methods

B. Comparative Study of 3D Images Method

In this last comparison, we compared the facial feature points detection methods using 3D images, such as Gabor Wavelet (GW), CLM, FAPD and Multimodal Facial Feature Extraction (MFFE). Fig. 11 shows the average detection rate of 3D facial feature points detection using a 3D mathods. This figure summarizes the results of this comparative study, comparative analysis of the graph shows that Gabor Wavelet (GW) encapsulates high accuracy and high efficiency. GW is the best method compared to other methods with an average detection rate of 99

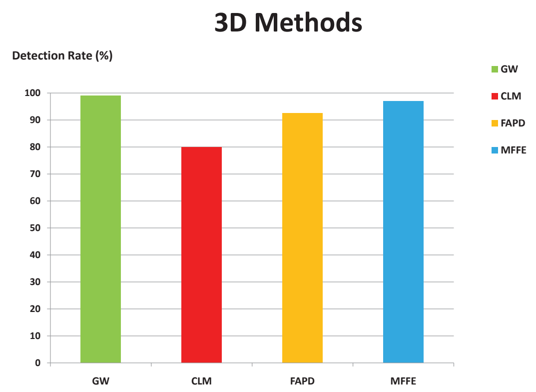

Fig. 11 Comparative study of average detection rate of 3D methods

V. Conclusion

Facial feature points detection plays an important role in applications such as facial feature tracking, human-machine interaction and face recognition. In this paper, we attempted to provide a comprehensive survey of current researches on this problem. Firstly, we presented a facial feature points detection methods using 2D images such as, GFBBC, FS-LFC, HOGGPM, AFM and SUSAN-O. Secondly, we described the methods of this problem with a three-dimensional images like Gabor Wavelet (GW), CLM, FAPD and Multimodal Facial Feature Extraction (MFFE). There are many advantages and disadvantages for these algorithms. After summarization for these techniques (Fig. 10 for 2D methods and Fig. 11 for 3D techniques), we can choose the better methods. Fig. 10 shows that the best method is SUSAN-O using Tokyo University Harashima Lab.'s face database with complex background with an average detection rate of $95,942\%$ and Fig. 11 shows that Gabor Wavelet (GW) is the best method compared to other methods with an average detection rate of 99%.

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