Face Sketch Recognition: Gender Classification and Recognition

Khalid Ounachad, Mohamed Oualla, Abdelalim Sadiq and
Abdelghani Sohar

Abstract--- *The main objective of this paper is to identify the gender of the human being based on their face sketch by using a geometric feature. This paper presents a novel method for human face sketch gender classification and recognition. We generate tow referential faces suitable for each kind of facial gender based on perfect face ratios and five classical averages. The basic idea is to extract perfect face ratios for the input face sketch and for each referential face as features and calculate the distance between them by using fuzzy hamming distance. To extract perfect face ratios, we use the point landmarks in the face then sixteen features will be extract. An experimental evaluation demonstrates the satisfactory performance of our approach on CUHK Face Sketch dataset (CUFS). It can be applied with any existing face sketch dataset. The proposed algorithm will be a competitor of the other proposed relative approaches. The recognition rate reaches more than 88, 60% for female and more than 86, 70% for male.*

Keywords--- *Face Sketch, Facial Gender Recognition, Perfect Face Ratios, Average Face Ratios, Fuzzy Hamming Distance.*

I. INTRODUCTION

Facial gender recognition (FGR) became an important topic in the fields of computer vision and artificial intelligence owing to its utility in social platforms, social media, commercial profiling, human-computer interaction and identification of a person in the process of detection of the Criminal in the criminology. They are two basics kinds of gender: Female and Male (Ekman, 1987). People's face is the most exposed part of body. Gender is one of the most important attributes of face. People, can immediately recognize the gender of a person. It is an easy task for humans to classify gender but challenging task for machines. Gender classification can be used as part of a face recognition process.

Face Gender Recognition systems (FGR) aim to recognize a gender in a dataset of photos or sketches images. The task of gender recognition is particularly difficult: There doesn't exist a large dataset of training sketches images and classifying gender can be also difficult. In a face gender recognition system Figure1, the feature extraction is the core block. Matching is used to recognize the right kind of gender using the precomputed features. The pre-processing step can boost the final performance of the system considerably. Feature extraction aims to transform the input face gender sketch into a set of features.

Khalid Ounachad, Department of Informatics, Faculty of sciences, Ibn Tofail University, Kenitra, Morocco. E-mail: khalid.ounachad@uit.ac.ma
Mohamed Oualla, SEISE: Software Engineering & Information Systems Engineering Team, Faculty of sciences and technology, Moulay Ismail University, Errachidia, Morocco. E-mail: mohamedoualla76@gmail.com
Abdelalim Sadiq, Department of Informatics, Faculty of sciences, Ibn Tofail University, Kenitra, Morocco. E-mail: a.sadiq@uit.ac.ma
Abdelghani Sohar, Department of Informatics, Faculty of sciences, Ibn Tofail University, Kenitra, Morocco. E-mail: houssouhar@gmail.com

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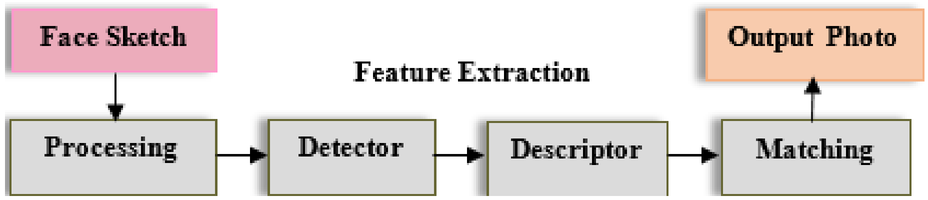

Figure 1: A generic diagram to perform face sketch recognition. Pre-processing boosts the Performance

Feature Extraction is the Core Block and Matching is used to find the Right Correspondences within Facial Images Using the Recomputed Features

Matching is a general concept to describe the task of finding correspondences between two elements that has to be carried out for recognition or classification. It can attempt a simple comparison between the features extracted or more complex comparison systems by using some distances.

The objective of this paper is to propose our method based on fuzzy hamming distance with average face ratios to recognizing a face sketch gender. This paper presents a novel method for human gender classification and recognition. We generate two referential faces suitable for each kind of facial gender based on perfect face ratios and some classical averages: arithmetic mean, geometric mean, harmonic mean, contra harmonic mean and quadratic mean. The basic idea is to extract perfect face ratios for the input face sketch and for each referential face as features and calculate the distance between them by using fuzzy hamming distance. To extract perfect face ratios, we use the point landmarks in the face then sixteen features will be extract. To compute distances between the input facial gender image and each image in a set of our referential faces sketches, the hamming distance based on logical exclusive-or (XOR) function is used.

The Hamming distance evaluates the number of bits that differ from two binary vectors. The Fuzzy Hamming distance (Bookstein, 2001) has been published to solve Hamming distance limitations on float numbers. This distance is used in this work because real values features are computed, not binary numbers. It ensures great performances in terms of speed and accuracy.

This article is organized as follows. Section 2 related works and background information about four classical averages, perfect face ratios and fuzzy hamming distance, their formalisms and their definitions, section 3, the proposed architecture of our approach is explained in depth. Experimental results are given in section 4. In section 5, a conclusion is presented.

II. RELATED WORK

Over the last decades, there has been a wealth of research in hamming distance, as well as in its application in computer vision specially in Face Sketch recognition (Ounachad, 2018), in Banknote Validator (Ionescu, 2005), in Content-Based Image Retrieval System (CBIRS) (Ionescu and Ralescu, 2005) and in Facial Emotion Recognition (Ounachad-MISC, 2018).

In (Ounachad, 2018) we presented a new facial sketch recognition method based on fuzzy hamming distance with geometric relationships (face ratios). We proposed to simplify the procedure based on fuzzy hamming distance to use only vectors with simple reals values of characteristics. An interesting contribution of (Ounachad, 2018) is

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that can accurately recognize the photo of the sketch's face. The proposed algorithm will be a competitor of the other proposed relative approaches. The recognition rate reaches 100% especially in the CUHK dataset.

The Fuzzy Hamming Distance based approach, proposed in Banknote Validator (Ionescu, 2005), combines the versatility of an automatic system with basic banknote specific information. Subsequently, the system can be updated to use in-depth security features provided by an expert. fuzzy Hamming distance is used to measure the similarity between banknotes

The study suggested by M. Ionescu et al. (Ionescu and Ralescu, 2005) (Ionescu, 2004) presented initial results on a new approach to measure similarity between images using the notion of Fuzzy Hamming Distance (FHD) and its use to CBIR. The main advantage of the FHD is that the extent to which two different images are considered indeed different can be tuned to become more context dependent and to capture (implicit) semantic image information. The study shows good results using complete linkage agglomerative clustering. Fuzzy Hamming Distance proved to be efficient in a Content Based Image Retrieval system, that output the closest images in the database given a query image. In (Ionescu, 2004), the obtained results for image retrieval based on using hamming distance showed effectiveness of their approach.

In (Ounachad-MISC, 2018), we present a novel method for human emotion classification and recognition. We generate seven referential faces suitable for each kind of facial emotion based on perfect face ratios and some classical averages. The basic idea is to extract perfect face ratios for emotional face and for each referential face as features and calculate the distance between them by using fuzzy hamming distance. To extract perfect face ratios, we use the point landmarks in the face then sixteen features will be extract. An experimental evaluation demonstrates the satisfactory performance of our approach on WSEFEP dataset. The recognition rate reaches more than 90%.

Contribution: This article proposes a new facial gender recognition method based on fuzzy Hamming distance with face ratios and their geometric relationships. Our work is inspired in part by the recent and successful method that has shown that relatively simple benchmark features could be used to perform well in a fuzzy Hamming distance-based face gender recognition framework. In this paper, we simplify the procedure based on fuzzy hamming distance to use only vectors with simple float values of characteristics. A key technical contribution of our paper is a method for recognizing a facial gender based on these simple features that can accurately recognize the right kind of the gender's face. This method achieves our goal by producing a recognition rate reaches more than 88%.

III. BACKGROUND INFORMATION

Symbolically, we have a data set containing the n values $x_1, x_2, \dots, x_n$.

3.1 Arithmetic Mean

The arithmetic mean (Average) (Ounachad, 2018) is defined as the average A:

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$$A = \frac{1}{n}\sum_{i=1}^{n} x_i = \frac{S}{N} \qquad (1)$$

$N =$The number of items being averaged.

$S =$The sum of the numbers being averaged.

It's equal to the sum of all n_numerical values of a set divided by the number of items in the set.

3.2 Geometric Mean

The geometric mean (Ounachad, 2018) is defined as the average G:

$$G = (\prod_{i=1}^{n} x_i)^{\frac{1}{n}} = \sqrt[n]{x_1 x_2 \dots x_n} \qquad (2)$$

It's the nth root of the product of n numbers, for a set of numbers.

3.3 Harmonic Mean

The harmonic mean (Ounachad, 2018) is defined as the average H:

$$H = \frac{n}{\sum_{i=1}^{n} \frac{1}{x_i}} \qquad (3)$$

It's the reciprocal of the arithmetic mean of the reciprocals of the given numbers.

3.4 Harmonic Mean

The contraharmonic mean (Ounachad, 2018) is defined as the average C:

$$C = \frac{\frac{x_1^2 + x_2^2 + \cdots + x_n^2}{n}}{\frac{x_1 + x_2 \dots + x_n}{n}} = \frac{x_1^2 + x_2^2 + \cdots + x_n^2}{x_1 + x_2 \dots + x_n} \qquad (4)$$

It's the arithmetic mean of the squares of the values divided by the arithmetic mean of the values.

3.5 Quadratic Mean

The quadratic mean (Ounachad, 2018) is defined as the average Q:

$$Q = \sqrt{\frac{x_1^2 + x_2^2 + \cdots + x_n^2}{n}} \qquad (5)$$

It's calculated as the square root of the mean of the given numbers.

3.6 Hamming Distance

Let F is a finite field with q elements.

The Hamming distance (Ounachad, 2018) (Ionescu, 2005) d(x, y) between two vectors x, y ∈ F(n) is the number of coefficients in which they differ,

$$d(x, y) = \text{Card}\,\{i \,/\, x_i \neq y_i\} \qquad (6)$$

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3.7 Degree of Difference

The Degree of difference (Ounachad, 2018) (Ionescu, 2005): Given the real values x and y, the degree of difference between x and y, modulated by $\alpha > 0$, denoted by $d_\alpha(x,y)$ is defined as:

$$d_\alpha(x,y) = 1 - e^{-\alpha(x-y)^2} \qquad (7)$$

The parameter α modulates the degree of difference in the sense that for the same value of $|x-y|$, different values of will result in different values of $d_\alpha(x,y)$.

3.8 Difference Fazzy Set

The Difference fuzzy set for two vectors (Ounachad, 2018) (Ionescu, 2005): Let x and y be twon-dimensional real vectors, and let xi, yi denote their corresponding ith component. The degree of difference between x and y along the component i, modulated by the parameter α is $d_\alpha(xi, yi)$. The difference fuzzy set corresponding to $d_\alpha(xi, yi)$ is $D_\alpha(x,y)$ with membership function:

$$\mu_{D_\alpha}(x,y)(i): \{1, \dots, n\} \to [0,1]$$
$$\mu D_\alpha(x,y)(i) = d_\alpha(xi, yi) \quad (8) \qquad (8)$$

$\mu D_\alpha(x,y)(i)$is the degree to which the vectors x and y are different along there ith component.

3.9 Cardinality of a Fuzzy Set

The Cardinality of a fuzzy set (Ounachad, 2018) (Ionescu, 2005):

Let: $A \equiv \sum_{i=1}^{n} xi/\mu i$ denote the discrete fuzzy set A over the universe of discourse $\{x1, \dots, xn\}$ where $\mu i = \mu A(xi)$ denotes the degree of membership for xi to A. The cardinality, $CardA$, of A is a fuzzy set:

$$CardA \equiv \sum_{i=1}^{n} \frac{i}{\mu_{Card(A)}(i)} \qquad (9)$$

Where: $\mu_{Card(A)=\mu_{(i)} \wedge (1-\mu_{(i+1)})}$

Where $\mu_{(i)}$ denotes the ith largest value of μi, the values $\mu_{(0)} = 1$ and $\mu_{(n+1)} = 0$ are introduced for convenience, and ^ denotes the min operation.

The non-fuzzy cardinality $nCard(A)$,is:

$$nCard(A) = card\left(\{x; \mu_{(A)}\ (x) > 0.5\}\right) \qquad (10)$$

Where for a set S, $\overline{S}$ denotes the closure of S.

3.10 Fuzzy Hamming Distance

The fuzzy Hamming distance (Ounachad, 2018) (Ionescu, 2005) between x and y, denoted by $FHD_\alpha(x,y)$ is the fuzzy cardinality of the difference fuzzy set, $D_\alpha(x,y)$:

$$\mu_{FHD(x,y)}(.\alpha): \{1, \dots, n\} \to [0,1] \qquad (11)$$

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$$\mu_{FHD(x,y)}(k,\alpha) = \mu_{CardD_{\alpha}(x,y)}(k)$$

For $k \epsilon \{1, \dots, n\}$ where $n = |SupportD_{\alpha}(x,y)|$

for a given value k, $\mu_{FHD(x,y)}(k,\alpha)$ is the degree to which the vectors x and y are different on exactly k components (with the modulation constant α).

3.11 Perfect Face Ratios

Based on the rules used to choose the perfect face (Ounachad, 2018), based on the ideas of the famous Italian doctor one of the fonder of criminology and based also on THE IDEAL PROPORTIONS OF THE FACE described by rhino plastic doctors, the ratios of the distances taken as the scientific measuring guns of the beauty in a perfect face are calculated. The same distances are computed for each face sketch in dataset of the face sketches.

The different distances used to calculate the proportions of the face are inspired by the scientific rules used to select the beauty queen. We define the following distances as:

d0:	The face width
d1:	The distance between the end of the right eye and the right end of the face
d2:	The length of the right eye
d3:	The distance between the eyes
d4:	The length of the left eye
d5:	The distance between the end of the left eye and the left end of the face
d6:	The distance between the centers of the pupils
d7:	The mouth length
d8:	The distance between eyes
d9:	The nose width
d10:	The mouth length
d11:	The jaw length
d12:	The distance between the eyes and the last point of the head
d13:	The distance between the eyes and the chin
d14:	distance between the center of the forehead and the last point of the head
d15:	The distance between the center of the forehead and the nose
d16:	The distance between nose and the chin
d17:	The distance between the eye and the eyebrow
d18:	The length of one eye
d19:	The distance between the low lip and the chin

IV. APPROACH

Our system has two modes, in both them, the input facial gender sketch and all faces sketches gender photos of the dataset are converted to a Gray level, they are resized and cropped into 100x125 pixels. These dimensions are chosen: It's the proposed default choice of the datasets used and it's also the dimensions used in the related works. The Viola and Jones algorithm (Viola, 2001) is used for detecting the face in each face sketch image. The first step of the system is to pretrain and to normalize all photos in the offline phase. For that they have been transformed into a gray level image and are all cropped to 100x125 pixels. The same technique is thus used to online mode. After this step, we projected the famous algorithm of viola and jones to detect the faces of the sketch images. The process that follows this second step is used to locate the 68_point_landmarks (Kazemi, 2014) in each face. These 68 points will be the parameter of our descriptor which allows to extract an identity of each face via the calculation of the rations

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of the perfect face. A vector will be dedicated to group these harmonious distances in order. This vector represents a real proportionality with any other similar vector. The ratios of these distances in the vector have been stored as already detailed in this section.

An overview of our proposed Fuzzy Hamming Distance based framework for face sketch gender recognition is shown in Figure 4.

In online process of the Face sketch gender Recognition System, given a facial sketch, sixteen features are extracted. The series of these characteristics composes a vector of real values.

This vector is considered as an identifier of the face sketch from which the values have been extracted and calculated.

In offline process of the Facial sketch gender Recognition System, we grouped the dataset of facial sketch photos into two data subsets based on the kind of gender that it represents. The same distances (used in online process) are extracted and calculated for each facial sketch photo for each data subset in the facial sketch gender dataset. We generate two referential faces suitable for each kind of facial sketch gender based on the classical means or averages: Arithmetic mean, Contra harmonic mean, Geometric mean, Harmonic mean and quadratic mean. We use the landmarks points the generate all referential faces.

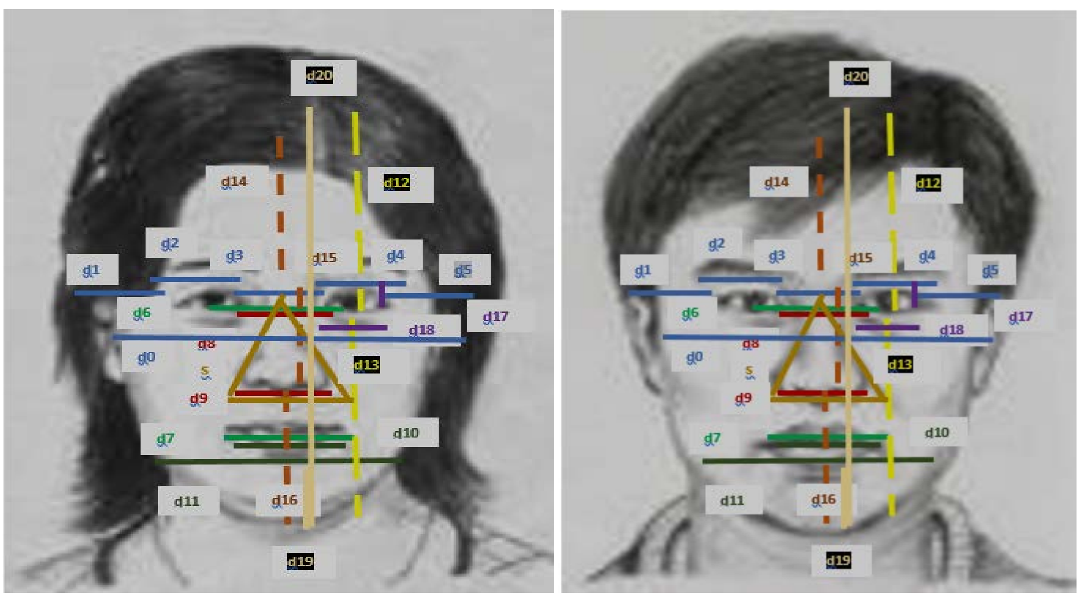

Figure 2: The different Distances Used to Calculate the Ratios of the Face for a Female and for a Mane. They are Described in Part 4 below and also are Inspired by Cannons in Perfect Face Ratio

After such a facial sketch gender photos and referential faces transformation to vectors of reals values, Facial sketch gender recognition becomes straightforward. We can compare the facial sketch with the referential facials gender using the Fuzzy Hamming Distance. In fact, we first compute the landmarks points for each facial sketch image and also for all referential faces of gender. The face ratios for each one is then used as feature vectors for final classification and recognition.

The algorithm contained eight steps, the detail of algorithm can be summarized as follows.

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1. To pretrain and to normalize all the facial sketch photos
2. Extract the landmarks points of the facial sketch photos according to the model “The 68_face_landmarks"
3. Calculate the distances d0 to d20 as defined in section IV.

we assume that:

$x_1 = \frac{d1}{d0}$	$x_2 = \frac{d2}{d0}$	$x_3 = \frac{d3}{d0}$	$x_4 = \frac{d4}{d0}$
$x_5 = \frac{d5}{d0}$	$x_6 = \frac{d6}{d7}$	$x_7 = \frac{d8}{d9'}$	$x_8 = \frac{d10}{d11}$
$x_9 = \frac{d12}{d13}$	$x_{10} = \frac{d14}{d20}$	$x_{11} = \frac{d15}{d20}$	$x_{12} = \frac{d16}{d20}$
$x_{13} = \frac{d17}{d18}$	$x_{14} = \frac{d19}{d20}$		

1) Calculate S: the surface of the nose (See Figure 3)

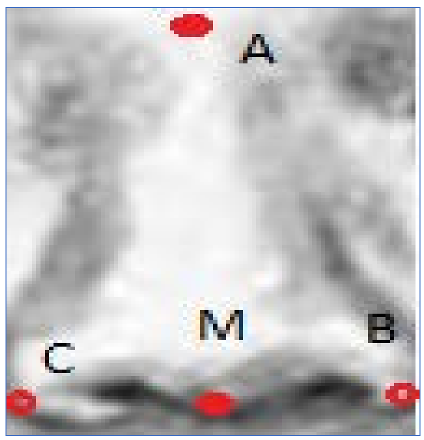

Figure 3: The Principle used for the Calculation of S: the Surface of the nose in a face sketch. S is based on the Manhattan distance Used here to Calculate the Sides of the Triangle Encompassing the Nose

The Manhattan distance is used here to calculate the sides of the triangle encompassing the nose.

Let:

$\boldsymbol{a} = \text{The distance between A and B (Figure3)}$

$\boldsymbol{b} = \text{AC distance}$

$\boldsymbol{c} = \text{BC distance}$

$\boldsymbol{A1} = (a + b + c)$

$\boldsymbol{B1} = (a + b - c)$

$\boldsymbol{C1} = (-a + b + c)$

$\boldsymbol{D1} = (a - b + c)$

$$\boldsymbol{S} = \frac{1}{4}\sqrt{\boldsymbol{A1.B1.C1.D1}} \qquad (12)$$

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We define: $x_{15} = S$

2) let:

- E= The tragus center of the ear
- I= Center inter eyebrow
- F= Center of the front
- C= The chin
- N= Dorsum of nose

The following angles are calculated:

$$\theta 1 = \overline{FEI} = \frac{arc\cos(EF^2 + EI^2 - FI^2)}{2 * EF * EI} \quad (13)$$

$$\theta 2 = \overline{IEN} = \frac{arc\cos(EN^2 + EI^2 - NI^2)}{2 * EN * EI} \quad (14)$$

$$\theta 3 = \overline{NEC} = \frac{arc\cos(EN^2 + EC^2 - NC^2)}{2 * EN * EC} \quad (15)$$

$$x_{16} = \frac{\theta 1 + \theta 2}{\theta 3} \quad (16)$$

Then:

$$x_{16} = \frac{\frac{arc\cos(EF^2 + EI^2 - FI^2)}{2 * EF * EI} + \frac{arc\cos(EN^2 + EI^2 - NI^2)}{2 * EN * EI}}{\frac{arc\cos(EN^2 + EC^2 - NC^2)}{2 * EN * EC}} \quad (17)$$

3) Create the vector: $V = xi,/i \in \{1, \dots, 16\}$

4) Compute FHD between Vi (the vector of the input facial sketch photo) and each vector Vf in the list of referential faces vectors; Their FHD is the same as that between the vector 0 and |x-y|. Therefore, the FHD between x and y is the cardinality of the fuzzy Return set D(|x-y|,0).

5) Recognition: The output is the kind of gender of the min distance for the referential face sketch parameter.

V. Experiments and Results

To demonstrate the effectiveness of the proposed method, we proceeded for acquiring the dataset of forensic hand drawn sketches. We used CUHK Face Sketch student dataset, the Chinese University of Hong Kong Face Sketch (CUFS) dataset (Ounachad, 2018) (Ounachad-BDCA, 2018) (Martinez, 1998). It includes 606 faces sketches in total.

We divide the dataset to two data subsets suitable for each kind of basics kinds of gender: Female and Male, TABLE 1 shown the percentage of each kind of gender.

The CUHK is used to training and to testing our approach. Figure 6 clearly illustrates step by step the results obtained as we progress in the process of the framework already described previously.

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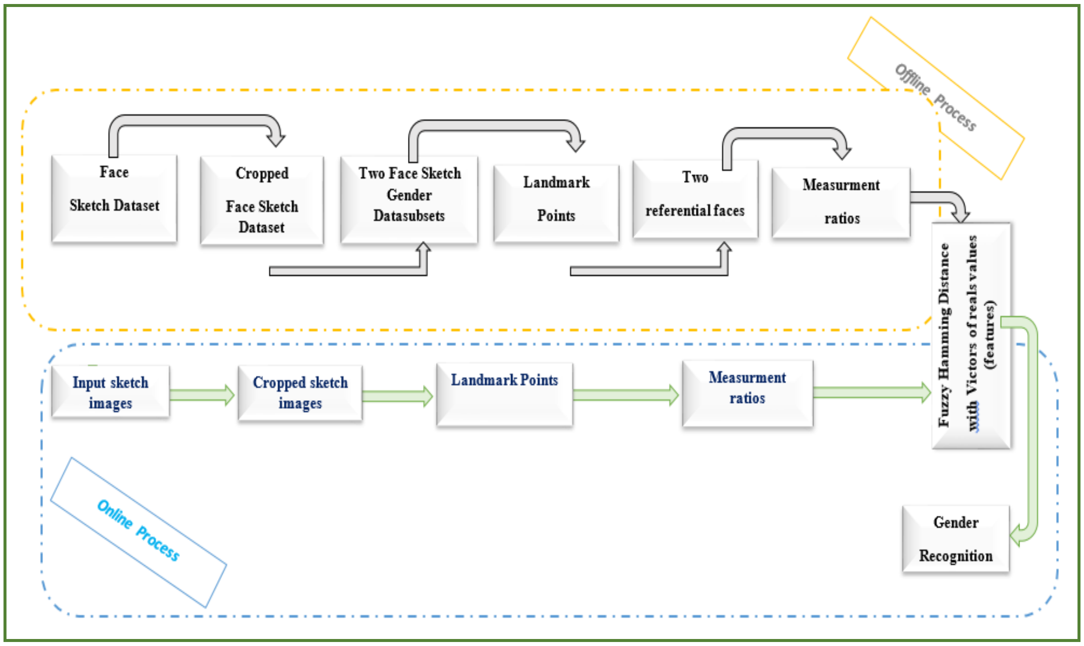


Figure 4: An overview of our proposed framework baseed on fuzzy hamming distance with face ratios for facial sketch gender recognition. (Given an input face sketch: Converted to gray level and cropped to 100x125 the facial sketch (100x125 is the standard size chosen in the relative database), detected the face and localized 68 landmarks points. Sixteen features are calculated based on the portions of the perfect face and an array of them is generated. These steps are similar between the two modes of face sketch gender recognition system FSGR. In offline process of FSGR ,the system can associate the right kind gender for each input image: The parameters of Fazzy Hamming distance are the extracted features from the facial sketch image and the referential faces gender, on the other side of the system , the generated vector from the facial sketch is involved to recognize its kind of gender. The output result of our FSGR is the probe kind of gender.)

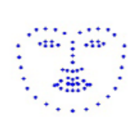
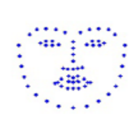
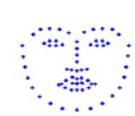
Means / Gender	Arithmetic mean	Geometric mean	Harmonic mean	Contraharmonic mean	Quadratic mean
Female					
Male					

Figure 5: Our referentiels 68_face gender_landmarks attributed to their kind of gender and the kind of mean used to calculate its, each model containbed: "Mouth", "Right_Eyebrow", "Left_Eyebrow", "Right_Eye","Left_Eye", "Nose" and "Jaw".The images for the usuel means are in the first and in the seconde colounms .

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Table 1: The Percentage of each kind of Gender from CUHK Dataset

Gender	Female	Male
Percentage	50.00%	50.00%

For each gender, in the first step the extract face sketch of the dataset. In the second: The cropped Faces sketches. In the third: The extract 68 face landmarks points. In the fourth: calculate of the sixteen features and in the last step: the vector generated from the facial sketches, it is involved to recognized the kind of the facial gender in the input photo of face sketch. The output result of FGR system is the probe kind of gender.

We generate two referential faces suitable for each kind of facial gender based on perfect face ratios and five classical averages: arithmetic mean, geometric mean, harmonic mean, contraharmonic mean and quadratic mean. The result is 10 referential faces. Figure 5 shown our referential face landmarks photo for each type of average. The images for Female are in purple and they are in bleu for the male gender.

Using our new method, we realized five experiments according to the average used during the generation of the referential face. In each one of them, we compare the input facial sketch gender image (features) with the two referential faces, for that we used the Fuzzy Hamming distance. The output probe kind of gender is that proper to the referential face having the minimal distance. TABLE 2 shows the cumulative match scores for our approach based on Fuzzy Hamming Distance (FHD) and Average Face Ratios. The result can be considered as a benchmark for the facial sketch gender recognition system to compare. All experimental results of tests are shown in Figure6. The cumulative match score is used to evaluate the performance of the algorithms. It measures the percentage of the probe gender.

TABLE 2 reports the facial sketch gender recognition accuracies using five different methods: arithmetic mean, geometric mean, harmonic mean, contra harmonic mean and quadratic mean. Our algorithm proves that, the recognition rate reaches more than 88.60% for female and more than 86.70%.

Figure 6: The process of our FSR, line1: extract of the dataset photos/input facial emotion. Line2: cropped emotional photos. line3: extract the 68 face landmarks points. Line 4: calculate of sixteen features and line5: the vector generated from the facial emotion photos, it is involved to Recognized the kind of Emotion. The output result of FER is the probe kind of Emotion of the Input Facial Photos

The figure.7 shows the cumulative match scores for our approach, it shows the gender recognition rate from face sketch using five classical means. The x-axis represents the kind of the used average and the y-axis represents the

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recognition rate. The results clearly demonstrate the superiority of our algorithm to recognize the females but the last rate of recognition is that of the male gender. The arithmetic mean helps to recognize the female and the male gender with the same recognition rate, it's 86.75%. The other means have different recognition rate.

Table 2: The Cumulative Match Scores for our Approach based on Fuzzy Hamming Distance (FHD) and Average Face Ratios (AFR)

Gender / Averages	Female	Male
Arithmetic Mean	86.75	86.75
Geometric Mean	88.61	86.75
Harmonic Mean	88.61	86.75
Contra_Harmonic mean	88.61	86.75
Quadratic Mean	88.61	86.75

The geometric mean, the harmonic mean, the contra_harmonic mean and the quadratic mean help to better recognize the female gender, but the arithmetic mean is not able to better recognize it. All means helps to recognize the male gender with the same recognition rate and with some accuracy. The geometric mean helps to better recognize the female gender but it helps to recognize the latest recognition rate of male gender. The harmonic mean and contra-harmonic mean aren't able to better recognize the male gender. The quadratic mean helps to better recognize the female gender but not able the recognize the male gender.

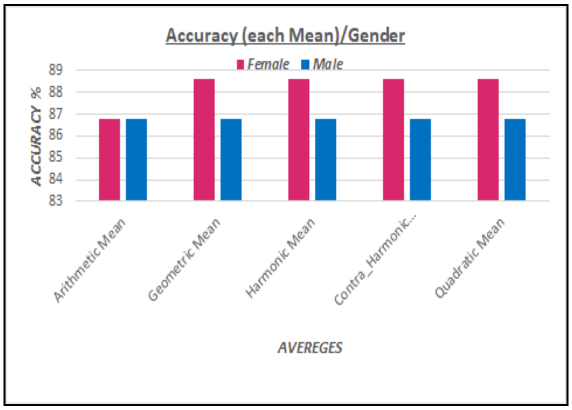

Figure 7: Comparison of Cumulative Match Scores between our Various Facial Sketch Gender Recognition Methods Using Five Clasical Averages

We tested our approach with five different facial emotion recognition methods using classical averages and Fuzzy Hamming distance. In these methods, the cumulative match score proves the performance of the algorithms. The recognition rate reaches more than 88,5% in CUHK dataset. The algorithmic complexity of our approach is O(n).

To use our algorithm perfectly:

- Large and labeled dataset is needed.
- A structured and multiple computing power are required for training.
- Large memory, powerful operating system and efficient platform are demanded.

VI. Conclusion

This paper proposes a new geometrical method for facial gender recognition. The methods are based on Fuzzy

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Hamming Distance and the Referential Face Ratios. We used sixteen features based on the distance between different portions of the perfect face. We tested our method on CUFS dataset and the results is very satisfactory. Our work is inspired by the recent successful methods that showed that relatively simple geometrics features could be used to give good performance in a Fuzzy Hamming Distance -based framework. Our approach can be useful in the process of identification of the criminal and the future work will include a decrease in the number of the features used. The feature work will include also a comparison of our algorithms with other algorithms on the domain.

REFERENCES

[1] P. Ekman and W.V. Friesen, 1987, "Universals and cultural differences in the judgements of facial expressions of emotion", *Journal of Personality and Social Psychology*, vol. 53.

[2] A. Bookstein, S.T. Klein and T. Raita, 2001, "Fuzzy Hamming Distance: A New Dissimilarity Measure". *Springer-Verlag Berlin Heidelberg, LNCS 2089*, pp. 86–97.

[3] K. Ounachad, A. Souhar and A. Sadiq, 2018, "Fuzzy Hamming distance and Perfect Face Ratios based Face Sketch Recognition", *IEEE International Congress on Information Science and Technology (CiSt)*, in press.

[4] M. Ionescu and A. Ralescu, 2005," Fuzzy Hamming Distance Based Banknote Validator", *IEEE International Conference on Fuzzy Systems*, June.

[5] M. Ionescu and A. Ralescu, 2005, "Image clustering for a fuzzy hamming distance based cbir system". *Midwest Artificial Intelligence and Cognitive Science Conference. Dayton*, pp 102–108.

[6] M. Ionescu and A. Ralescu, 2004, "Fuzzy Hamming Distance in a Content-Based Image Retrieval System", *IEEE International Conference on Fuzzy Systems* 3, vol.3, pp.1721–1726, August.

[7] K. Ounachad, A. Souhar and A. Sadiq, 2018, "Facial Emotion Recognition Using Average Face Ratios and Fuzzy Hamming distance", *International Conference on Modern Intelligent Systems Concepts (MISC), in press.*

[8] Viola P., Jones M.J, 2001," Rapid Object Detection using a Boosted Cascade of Simple Features". *IEEE CVPR*.

[9] V. Kazemi and J. Sullivan, 2014," One Millisecond Face Alignment with an Ensemble of Regression Trees", *IEEE, Computer Vision and Pattern Recognition (CVPR)*, September.

[10] K. Ounachad, A. Souhar and A. Sadiq, 2018, "A State of the art of Face Sketch Recognition", *Springer, International Conference on Big Data, Cloud and Applications, in press*.

[11] A.M. Martinez, and R. Benavente, 1998, "The AR Face Database", *CVC Technical Report #24*, June.

DOI: 10.37200/IJPR/V24I3/PR200860
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