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Dispersion Measures Describe Face Smoothness for Gender and Age Recognition

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Abstract

Face biometrics play a crucial role in describing gender and age changes. Male and female faces differ in terms of smoothness due to the formative properties, nature of lifestyle, and use of cosmetics. For age progression, faces record different levels of face vitality - from smooth face within childhood to wrinkles and folds in senior adult faces. This paper presents a set of dispersion measures to represent face features over gender and age variation. Besides, we inspect the exchanging effects between gender differences and life stages on the yielded results. These dispersion features are represented using localized formulas of statistical measures, such as Standard Deviation (SD), Statistical Ratio (SR) and Roughness Value (RV). Such statistical measures inspect the differences of image values regarding specific reference. The SD inspects the differences between a set of values and their average, while SR gauges the SD for set of values normalized by their average. The RV measure inspects the difference between the successive values normalized by their differences from the average. This paper adopts the localized forms of these measures to avoid the effects of the challenges (illumination and rotation) that dataset images suffer from. These adopted features provide significant discriminating powers over different ages and genders. The yielded results show that the adopted measures recorded mutual effects between age estimation and gender recognition.

Keywords: ***Face roughness, Dispersion measures, Age estimation, Gender recognition.***

1 Introduction

In the recent decades, face biometrics has gained significance in improved recognition performance. The importance of Age and Gender Recognition (AGR) is broad due to its correlation with different life applications. An intelligent application can be adopted by a seller in order to draw an accurate understanding about the customer class and

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corresponding suitable products. In addition, many laws and regulations determine that specific ages should be allowed to be a part of specific actions while others are not [1, 2]. A crucial tool in AGR researches is the human face, since it contains holistic, sufficient and complex information about the person [3].

Face roughness was considered as a significant factor in determining the age, gender, race or facial expression using human faces [4]. Due to the differences in gender and age stages, the human face differs in levels of smoothness due to formative properties, life style, facial hair and the usage of cosmetics. Figure 1 illustrates examples of obvious differences in face vitality of old and young, female and male persons. In addition, face smoothness is a considerable factor in determining real faces from plastic masks and photographs.

High levels of face roughness produce significant differences between image values, while smooth areas produce lower differences [5]. Figure 2 represents the differences between image values for samples from corresponding areas of the face. Samples were captured from similar forehead parts of female/male and young/ old faces using the same size for all samples. It is observed that the differences between the image values provides considerable features that describe image smoothness.

(a) Young/Old female (b) Young/Old male (c) Male/Female

Fig. 1: Samples of different level of face smoothness over gender/ age variation

There are many methods to gauge the differences between sets of values. An efficient technique is to use the Statistical Dispersion Measures (SDM), which computes a single number for an entire set of numbers. SDM inspects the differences between the numbers and converts them into dispersion results.

This paper adopts a set of SDM to inspect the differences between image values, to provide discriminative features for gender and age recognition. The rest of paper is structured as follows: Section 2 describes the adopted statistical measures, and Section 3 describes their localized forms. Section 4 provides the constructed classification scheme and the proposed methodology. Section 5 discusses the yielded results, with Section 6 providing the concluding remarks and recommendations for future work.

2 Statistical Dispersion Measures (SDM)

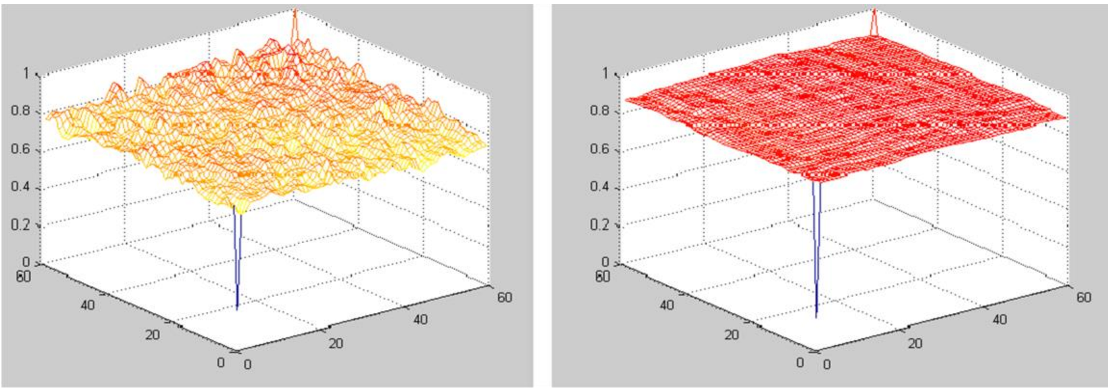
Statistical measures deal with sets of values to extract analytical, descriptive, and quantitative information (features) about them [6]. Dispersion (variability) measures gauge how the values are spread or propagated about each other or about a central point [7]. These measures have high values in the case of a wide spread, which indicates high roughness if these values represent a surface (e.g. face skin in this paper) [8]. Since SDM depend on differences between the values rather than the values themselves, features provided by SDM have the following advantages:

They are robust against illumination that affects the level of the image value [9], as they depend on the differences between the values rather than the values themselves. As an example, the dark image values 15, 43, 52 have significant distance from the ones from illuminated image 177, 192, 221. However, the differences between the dark image values (43-15=28 & 52-43=9) is a closer distance match with the illuminated image values (192-177=15 & 221-192=9).

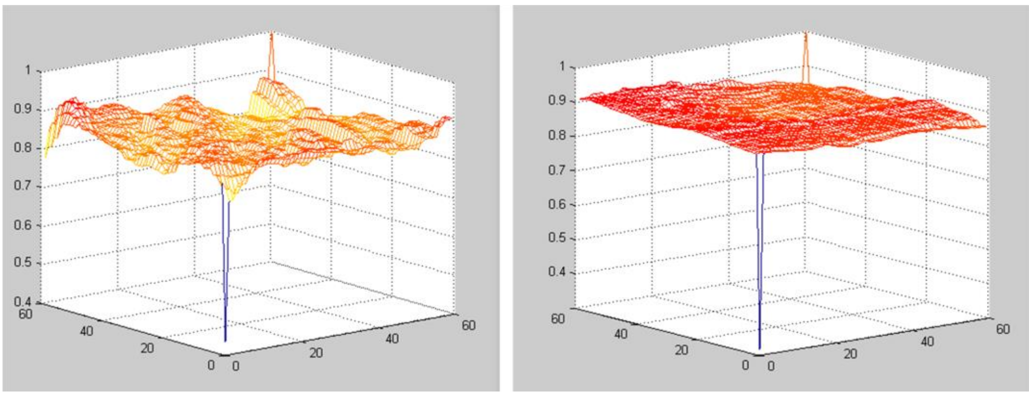
They are robust against rotation. For example, SDM provides one fixed value for a (5×5) mask even when it rotated in any direction.

SDM provides dimension reduction for image data when it produces a single value for a set of values, which saves a significant amount of time in the training stage.

Besides these, this paper also utilizes the localized form of the adopted SDM, which are described in the sections below. Three SDM are used to gauge the differences between set of values [10], i.e. Standard Deviation (SD), Statistical Ratio (SR), and Roughness Value (RV).



(a) Male face /no-hair area (b) Female face



(a) Old male face (b) Young male face

Fig. 2: Obvious differences in image values between old and young faces & female and male

2.1 Standard Deviation (SD)

The SD measure gauges the propagation of the values around their average using the summation of squared differences between sample values and their average normalized by the sample size. The SD measure is preferred over the original variance since it produces results with the original units, whereas the variance produces results with squared units. Assume the set of values y_i, where i=1, 2, 3, …, n, then the average of these values is given by:

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n}(y_i) \dots\dots 1$$

Where: $\bar{y}$ is the average, n is the sample size and y_i represents the image values. Then, SD computes the dispersion of image values (y_i) around their average ($\bar{y}$) as:

$$SD = \frac{1}{n-1}\sum_{i=1}^{n}(y_i - \bar{y})^2 \dots\dots 2$$

2.2 Statistical Ratio (SR)

The SR is the ratio between the SD and the average values for the same set of numbers. Although SD is robust against illumination (different levels of values), smooth surfaces from different areas can record different levels of SD, and the same situation is faced with rough surfaces. To resolve the issue, SR normalizes SD values by the average of the inspected values, which eliminate the effects of different values extracted from different areas. SR is calculated as follows:

$$SR = \frac{SD}{\bar{y}} \dots\dots 3$$

2.3 Roughness Value (RV)

Both SD and SR inspect the dispersion (or value differences) for the whole set of values as a single set. In some cases, differences from different image regions can eliminate (or reduce) the effects of each other. The RV discusses the detailed differences between the successive values, and these differences are normalized by the differences from the average. Such normalization reduces the effects of different-regions values, and the mathematical form for computing RV is given below:

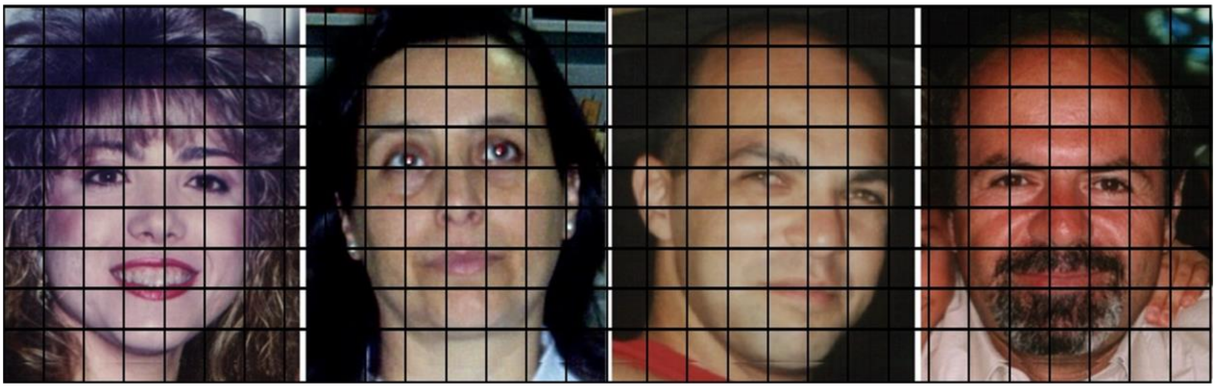
$$RV = \frac{\sum_{i=1}^{n}(y_i - y_{i-1})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \dots\dots 4$$

These SDM forms provide significant methods to inspect the dispersion between sets of values, yet their performance in gender and age recognition recorded degradation in the yielded results in the past [7 and 8]. As a result, this paper proposes a solution using the localized forms for the human face image.

3 LOCALIZED STATISTICAL DISPERSION MEASURES (LSDM)

Feature extraction for human face images requires techniques that consider illumination issues, face rotation cases, and different color regions. Variations of face color is affected by makeup and cosmetics, besides the nature of different face parts (eyes, opened/closed mouth and face hair), which have different colors [11]. Figure 3(a) illustrates the different regions of color in the typical human face image, which produces different regions of image values.

(a) Different regions of color in human face images



(b) Dividing the dataset images into blocks to extract LSDM for each block individually

Fig. 3: Dividing the image into regions provide more accuracy in dealing with different regions of

On the hand, inspecting the face smoothness requires detailed inspection for variation of image values to detect the detailed face roughness [12, 13]. The proposed LSDM method inspects the local dispersion of the values by considering the local differences.

3.1 Localized SD (LSD)

The SD measure produces one value for the whole set of values, which means a single value for the whole image. The different color regions provide different levels of image values. Different details of the human face and the different styles of variations provide fake dispersion when considering the whole image as one object [14]. For these reasons, this paper divides the face image into blocks and extracts LSD values for each block individually, as shown in Figure 3(b).

3.2 Localized SR (LSR)

Localizing SR has major dependence on localizing SD, yet computing LSR includes depending on the local average for each image block. This provides adopting a local relative average, which includes the local details without considering different details from other regions.

3.3 Localized RV (LRV)

Localizing the RV measure is accomplished in two ways: (1) the first one is by computing the measure for each block and avoiding the effects of other regions; (2) the second relates to the essential RV form (Equation 4), where the numerator computes the successive differences for all of the values and the denominator computes the differences of the same values from their average. Such a form provides a holistic view of the dispersion without detecting the local differences [15]. Mathematically, Equation 4 can be modified to the Equation 5 below, since the summation range is the same:

$$LRV1 = \sum_{i=1}^{n} \frac{(y_i - y_{i-1})^2}{(y_i - \bar{y})^2} \ldots\ldots 5$$

From the feature extraction perspective, the results will differ. Each difference between the successive values is normalized by the difference of the same single value from the average. This detects the detailed changes of image values, which means detecting each change in face smoothness/roughness. Equation 5 has a further localization, as illustrated in Equation 6. Where the power in the denominator and numerator of Equation 5 is the same, the difference between successive values is normalized by the difference from the average before squaring the amount.

$$LRV2 = \sum_{i=1}^{n} (\frac{y_i - y_{i-1}}{y_i - \bar{y}})^2 \ldots\ldots 6$$

Using such a form will indicate if the difference is an increment or decrement, which means moving to higher or lower color value. This modification provides more information about the color variation in the face image.

4 PROPOSED METHODOLOGY

This paper proposes a feature-based recognition system for human age and gender via face images. Age and gender are two factors that affect each other in face classification schemes, and studying them together allows consideration of their mutual effects. Proposed methodology of this work depends on two major parts LSDM and AGR. In LSDM, statistical measures are localized to provide discriminative features for age and gender recognition, where in AGR both gender recognition and age estimation are performed excluding the effects of each of them on the other. The overall proposed methodology is summarized in Figure 4 and described in the sections below.

4.1 Dataset

This work employs a face dataset containing two parts. The first one is the standard FGNET dataset for benchmarking purposes. Since the first part contains only 1002 face images, the second part containing an additional 2283 face images was collected from the Daily Digital Photography [16]. This second part of the dataset was added to enhance the training stage of the classification scheme.

4.2 Gender Recognition

Recognizing female faces from male ones was the center of focus over the many years due to its importance. Gender recognition is the process of deciding whether the studied face belongs to a female of a male person [17]. A face image presents significant information about the sexual identity, which provides efficient recognition about the person’s gender [18]. Skin Roughness still provides discriminant feature even when using face cosmetics, where image values differ even if the image looks smooth to the human eyes. These features provide indications about the biological signs in face attributes significant to efficiently recognize the face gender. To identify the face gender, previous works adopted different types of face features [19]. Some of them depended on the Progressive Calibration Network (PCN) and the standard Gabor filter [20]. Due to the effects of age progression, the authors studied gender recognition within age groups (adolescent and adult ages), and they ignored the senior adult ages. Others adopted the standard Viola Jones algorithm to detect the face and then combined Haar-like features with Adaboost [21]. Considering differences between image values was widely adopted in different forms such as in the Canny edge detection [22, 23], which is performed using image gradient and value differences [24]. On the other hand, some authors focused on determining the differences between female and male faces, where they studied the effects of these differences on the recognition process [25]. Besides human face, many biometrics were adopted for gender recognition, including iris, finger prints, and hand images [26-28] and others.

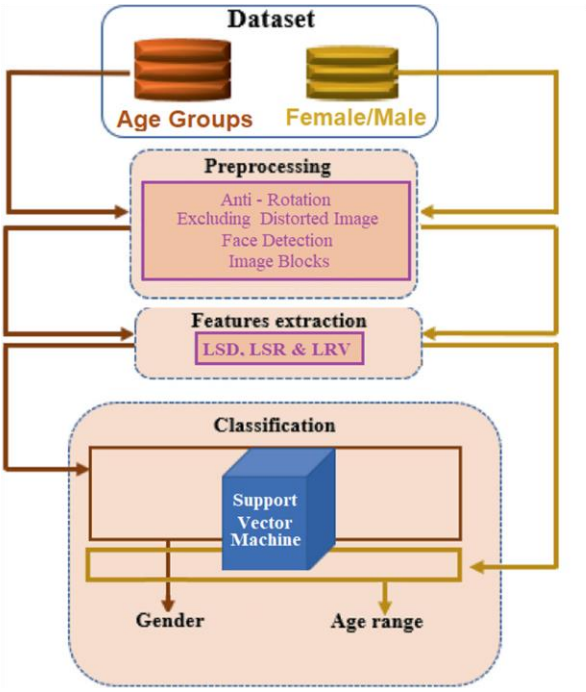


Fig. 4: The overall diagram for the proposed

4.3 Age Estimation

Age estimation algorithms determine the related age of a human face using different types of extracted features [29]. This branch of knowledge gained increasing attention in the recent decades. Some previous works proposed the topographical features that also depended on differences between image values in the form of 1st and 2nd gradient [30]. Using differences between image values for age estimation was inspired by face wrinkles, folds, and lines that are obvious in senior adult stages of age. These features produce high levels of differences within image values. In contrast, early stages of age provide high levels of face vitality with low levels of differences between image values [20]. Between those, the human face has a transitional stage of face smoothness. [31]. Different scales

and directions of texture features were gathered by Gabor Wavelet Transform (GWT), where the best set of them was selected using the hybrid method for feature selection. The authors trained and tested their features using the standard Support Vector Machine (SVM) classifier [32].
This paper proposes using face smoothness in the form of differences of image values, which are measured using the statistical measures of dispersion. Such features provide distinguishable levels of changes over face gender and age stages.

4.4 Classification Scheme

The proposed classification scheme for gender and age classification is divided into 3 main stages. The first stage is Preprocessing, which is subdivided into: excluding extremely distorted images, anti-rotation (rotation normalization), face extraction and dividing the image into blocks. Face images that are highly distorted are excluded in this work, focusing the experiments on moderately-distorted and high-quality images. Some dataset images were captured in poses where the head/face is angled in some other direction, which necessitate anti-rotation to the normalize them to the vertical pose [34]. The Viola Jones algorithm for face detection is used to ensure the desired Region of Interest (ROI) in this work [35]. Finally, the detected face is then divided into blocks to analyze each of them individually.
The second stage is Feature Extraction, which includes computing LSD, LSR, LRV1, and LRV2 measures for each image block independently, considering that each block eliminates the effects of different areas of color within the face and ensures that the dispersion value represents the roughness of image values. Such features ensure decreasing the illumination twice, firstly using the statistical differences between image values and secondly by computing dispersion measures for each block independently.
The third stage is the Classification, where the extracted features are trained and tested by using the SVM classifier. Due to the mutual effects between gender and age in the human face image, two types of classification schemes are employed. The first one is gender-age classification, where the age is estimated considering if the face is essentially for a female or male person. This scheme considers that age progression effects on female faces have different levels of changes from male faces [2, 14]. The second scheme is age-gender classification, where the age is classified into periods of age and then the gender is classified for each age class independently. Such a scheme considers that each period of age has its own differences between female and male faces [4, 17].

5 RESULTS AND DISCUSSION

5.1 Evaluation Metrics

The yielded results in this paper are evaluated using the standard form of Result Accuracy (RA), which represents the number of correctly classified units divided by the total number of units [35]. This measure is adopted since it is computationally simple and provides a clear depiction of the performance. The correctly classified units include the True Positive (TP) and the True Negative (TN), normalized by the total number of units including the False Positive (FP) and the False Negative (FN). The RA is computed as follows:

$$RA = \frac{TP + TN}{TP + FP + TN + FN} \dots\dots 7$$

The data used in this work are the standard FGNET face dataset, augmented with the privately collected face dataset. The private set was added to support the quality of the handled images, where all of them were of high quality. The proposed classification scheme was trained on 3027 images as in Table 1, where the samples were selected to cover a range female and male faces of different age periods. The dataset images were divided into the widely adopted ratio, where 80% was used for the training and the remaining 20% used for testing, with cross-validation used for balancing.

Table 1: The adopted dataset distributed on different genders and ages

Age	Female	Male	Total
0-9	312	313	625
10-19	232	321	553
20-29	315	207	522
30-39	286	227	513
40-49	214	195	409
50-59	135	83	218
60-69	98	89	187
Total	1592	1435	**3027**

5.2 Age-Gender Classification

In this section, the dataset images are classified into age period using the ground truth (image labels). Then SVM training and testing are applied to classify the gender over each age period individually. Table 2 summarizes the results yielded by dispersion measures (LSD, LSR, LRV1 and LRV2), after considering the age (a), and before that (b). Such computation excludes the effects of the age period on gender classification. Each number inside the table represents the percentage of the images classified as female or male correctly.

Table 2: Explains the yielded results for gender recognition over each age period

Age	LSD %		LSR %		LRV1%		LVR2%	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
0-9	92.2	88.9	93.8	90.1	95.3	91.7	93.9	91.0
10-19	93.7	90.1	93.8	91.2	94.8	91.9	92.5	89.9
20-29	94.1	92.3	93.9	91.9	95.6	92.4	94.2	92.2
30-39	92.7	88.6	93.1	91.6	93.7	91.6	93.3	91.1
40-49	91.8	90.4	93.5	93.1	93.8	92.7	92.9	91.9
50-59	93.3	89.9	94.0	92.7	95.5	92.7	93.7	92.1
60-69	92.7	90.1	93.6	90.8	94.2	92.7	93.8	91.4

Note: (a) taking age into consideration, (b) not taking age into consideration

Yielded results in Table 2 provide some points that indicate the following; LSD yielded the lowest performance among the other localized measures. This is justified as LSD is the simplest form among the measures employed and it is not normalized by the mean of the values (cf. LSR). On the other hand, it does not discuss the successive differences like

LRV1 and LRV2. The best measure among them was the LRV1, since it considers each successive difference regarding the distance for the values average. The measure LRV2 yielded insignificant improvements from LRV1, whereas it yielded noticeable enhancements from LSD and LSR, but most of its results yielded lower performance than LRV1. This can be justified referring to the negative differences have ignorable effects due to the squared values.

Finally, considering age classes in classifying the gender yielded encouraging enhancement with regards to the original gender recognition operation. Table 3 summarizes the classification differences between after and before considering the age, and their average values. In other words, this table summarizes yielded enhancement in the classification results explained in Table 2. In Table 2, gender recognition within the age period (0-9) yielded 88.9% accuracy when SVM was training over the whole dataset, whereas it yields 92.2% when SVM trained on image of (0- 9) age only. Table 3 explains that LSD yielded 3.3% enhancement (92.2- 88.9), and with other cells, Table 3 provides an explanation about result enhancement for gender recognition before and after age consideration.

Table 3: Differences in classification of female and male faces over age periods

Age	**LSD %**	**LSR %**	**LRV1%**	**LVR2%**	**Average**
0-9	3.3	3.7	3.6	2.9	3.38
10-19	3.6	2.6	2.9	2.6	2.93
20-29	1.8	2	3.2	2	2.25
30-39	4.1	1.5	2.1	2.2	2.48
40-49	1.4	0.4	1.1	1	0.98
50-59	3.4	1.3	2.8	1.6	2.28
60-69	2.6	2.8	1.5	2.4	2.33
Average	2.89	2.04	2.46	2.1	**2.37**

5.3 Gender-Age Classification

This section adopts classifying the studied images into female and male using image labels, and then undertaking the training and testing for age estimation within each gender individually. Such classification eliminates the effects of gender differences on age estimation. Table 4 summarizes the RA results for age estimation within face gender, where each number within the table represents the percentage of correctly estimated ages for female and male faces independently.

Table 4: Results for age estimation over each female and male gender

Age	**LSD %**		**LSR %**		**LRV1%**		**LVR2%**	
	(a)	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**
Female	94.2	92.1	94.8	93.1	96.3	95.6	95.1	95.2
Male	93.6	91.8	94.7	94.3	95.8	94.9	95.5	94.9

Note: (a) taking gender into consideration, (b) not taking gender into consideration

In this table, the performance of LSD, LST, LRV1 and LRV2 were similar to their performance in Table 2, yet other changes were noted. Firstly, LSDM yielded better performance on age estimation than in gender recognition which indicates that face roughness has better discriminative powers on different ages than on different genders. Secondly, ensuring a fixed gender over the training and testing stages for age estimation recorded lower differences than ensuring fixed ages over gender recognition, as shown in

Table 5. In other words, age progression recorded higher effects on gender recognition than the gender affecting the age estimation. From the value changes observed in these tables, age estimation and gender recognition recorded mutual effects on each other.

Table 5: Summary of the difference of age estimation between after and before ensuring fixed gender

Age	LSD %	LSR %	LRV1%	LVR2%	Average
Female	2.1	1.7	0.7	0.1	1.15
Male	1.8	0.4	0.9	0.6	0.93
Average	1.95	1.05	0.8	0.35	**1.04**

6 CONCLUSION

In this paper, the proposed system is constructed for join classification of human gender and age. The major contribution of this paper is about using face roughness as a face descriptor to study gender changes and age progression. To describe the face roughness, statistical measures for dispersion were used. The images are divided into blocks to compute the measures for each block individually in order to avoid illumination effects. Another contribution is about enhancing the performance of these measures using the localized forms of them (LSDM), which focuses on the local differences between the values. The significance of these measures that they were enhanced to be robust against illumination and rotation. The last part of contribution is the considering of age periods to enhance the accuracy of gender recognition, and estimating human age within female and male images to enhance the classification performance. LSDM measures yielded encouraging performance, but the localized form of SD recorded the lowest level of performance. The highest performance was recorded by the localized form of the Roughness Value (LRV1), where the second version (LVR2) recorded encouraging performance with insignificant enhancement from LRV1. Face age and gender recorded mutual effects on each other, yet the age progression recorded higher effects on gender recognition than gender differences on age estimation. For future work, LSDM are candidate for dimension reduction. In addition, Deep Learning Networks (DLN) is also suggested as they could be candidates to represents such images in Deep Learning algorithms.

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