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An Analysis of Sexual Dimorphism in the Human Face

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Abstract

Human beings can distinguish between a male and a female face without much difficulty. The science of recognizing and differentiating different faces by humans is not completely understood and is still under research. Sexual dimorphism is common in humans and indeed in other species of animals as well. Significant differences between males and females exist in many aspects like size, color, body shapes, and weight. In this research, we characterize and analyze the sexual dimorphism in the human face as a function of age and of face features. Features are grouped into six categories: head, eyes, orbits, nose, lips, and mouth, and ears. We demonstrate that the face of adult males is significantly different from adult females. We also identify the features that significantly contribute to the dimorphism of the face. This provides a basis for gender-based classification of faces.

Keywords: face recognition, sexual dimorphism, gender classification, face classification, human face

1. Introduction

Human beings can distinguish between a male and a female face without much difficulty. Humans have intuitive ability which makes it possible to recognize the faces [1]. Though males and females differ in many characteristics, the face plays a significant role. However, a viewer often cannot describe the exact reason of how he could determine if a person is a male or a female. It is difficult to specify exactly the features and the reasons that enable a viewer to make the distinction. Face is an important feature of humans, as it plays a significant role in their activities. The notion of beauty is often associated with the face. A facial expression provides a guide to the disposition of a person and hence is important as well in the manner humans conduct social interaction. Detection, identification of faces, as well as facial expressions have been approached both theoretically and experimentally for several decades [2, 3]. The goal of this research is to study sexual dimorphism in humans with the focus on human faces. In particular, we would like to identify the features in faces that are most different in male and female faces. We use both direct measurements and photographic images of the face as the basis for our analysis.

1.1. Sexual size dimorphism in humans

The dictionary definition of dimorphism is “difference of form between members of the same species.” Sexual dimorphism, in general, refers to differences between males and females of the species in terms of size, appearance, and behavior. Dimorphism exists in various forms in all humans. Any person can easily observe dimorphism in humans by looking at a face. Studies have shown that parts of human anatomy exhibit sexual dimorphism. Factors and the features responsible for dimorphism in humans are still under research. The study aims to contribute the understanding of sexual dimorphism by analyzing the dimorphism in human face and identifying the features of the face that contribute to the dimorphism.

1.2. Applications

Research on sexual dimorphism can be used in conjunction with face recognition systems in several ways. It can
be used as a mechanism to reduce the search space by half, if the gender of the face is known in advance or can be determined automatically. In large databases this could result in significant reduction in search time. The research can be used for analyzing the facial expressions and determining the gender of the subject in the photograph.

1.3. Contributions

Specific contributions of this research are to: (a) add to the body of knowledge in sexual dimorphism, (b) provide quantitative results that measure sexual dimorphism in human faces and develop a basis that could be used to differentiate between male and female faces. In this research, we use both direct measurements and measurements from photographic images for our analysis. We also study how sexual dimorphism changes as a function of age and which features are more significant in the expression of sexual dimorphism. In addition, we analyze the features to determine which ones are likely to be most useful in automated analyses.

It should be noted here that our goal here is to fundamentally understand the degree and extent of sexual dimorphism in the human face. Therefore, we have relied on measurements obtained directly or indirectly from the human face by manual methods. There is an active research community in extracting features automatically and the results can seamlessly dovetail into the results from this research to develop a fully automated system to accurately classify faces into males and females. This information provides a guide to research into automated methods in the sense that the most important features of the face are identified. The results of this study may be used to tune some of the standard procedures in face recognition.

1.4. Organization

The paper is organized as follows. We summarize the previous research on sexual dimorphism in Section 2. In Section 3, we describe the datasets used in this research and how they are obtained. The fundamental research questions in sexual dimorphism in the face are posed, studied and analyzed in Section 4. Finally, we conclude with a summary and directions for future work in Section 5.

2. Background research

Face recognition can be defined as visual perception of familiar faces. The face is often regarded as the most important feature in humans. This is because the face acts as a guide for recognizing or identifying a person. Humans have the ability to easily detect and identify the difference between faces with little or no effort. The ease of recognition has led some researchers to hypothesize that humans have an inherent ability to recognize and differentiate faces [1]. A significant body of literature exists in face recognition and analysis of human faces. A detailed review of human face recognition is beyond the scope of the paper, but is provided elsewhere [2, 3].

2.1. Sexual dimorphism in humans

Sexual dimorphism can be defined as the systematic difference in form between individuals of different sex in the same species. Though any human being can distinguish the difference by appearance, it’s stated that human beings have comparatively lower level of dimorphism when compared to other species. In most of the species, the dimorphism manifests in the size. For instance, in mammals the male is usually larger than the female. Some of the other factors influencing the dimorphism among humans can be weight (studies indicate a normal male is 1.2 heavier than a normal female), height, hair, face, muscles (more among men than women), voices, body shapes, color, size of eyes, and behaviors [4].

2.2. Sexual size dimorphism

Sexual dimorphism when quantified using either differences or ratios is referred to as the “Dimorphism Index” and is commonly referred to as sexual size dimorphism index (SSDI), or simply as sexual size dimorphism (SSD). SSD helps us in determining the degree of difference between the male and female measurements. Many different ways to compute the SSD have been proposed in the literature [5]. An SSD value close to “0” indicates the feature is similar in males and females [6]. A positive value of SSD means that the male measurements are higher than the females. On the other hand, a negative value indicates that the female measurement is higher. It is observed that angular measurements have high SSD’s when compared to other direct linear measurements [7]. Features that have larger values in males tend to have lower SSD.

2.3. Sexual dimorphism in human face

The human face also plays a significant role in the sexual dimorphism. Researchers have studied human faces dating back to the renaissance period [8]. The focus then was to determine the most appropriate dimensions of human face for making beautiful sculptures. Studies have been conducted on different races to determine the dimorphism in the human face among different human races [9].

Ferrario et al. used the Euclidean distance matrix analysis method to determine the sexual dimorphism in the human face [10]. The method employs a two-step procedure; (a) calculate all the possible Euclidean distances between the selected points on a face; (b) compare the two faces by calculating the matrix of ratios of corresponding linear Euclidean distances measured on the faces. The study conducted the analysis on 108 adults (57 men, 51 women) and the results show significant sexual dimorphism among adult faces. In most of the cases it is observed that the female’s face is shorter when compared
to her male counterpart. Also, the middle and lower parts of face are observed to show more gender variation.

3. Datasets

We use two different datasets to analyze sexual dimorphism in the human face. A set of direct measurements from human faces was obtained from the literature [11]. However, not all our questions could be answered using this dataset. Consequently, we developed a mechanism to derive some measurements indirectly from a set of face images.

3.1. Direct measurements

Farkas compiled a set of measurements from faces as a part of a study to improve reconstructive surgery on deformed faces [11]. A set of canonical points on the face was identified and a set of distances that are critical in surgery are determined and measured. The distances were grouped into seven groups: head, face, orbits, nose, lips, mouth, and ears. A total of 2,326 Caucasian North Americans, with ages ranging from newborn to young adults (19-25) were used in this study to compile the measurements. The samples are almost equally divided between males and females. Data were collected from people living in western, central, and eastern provinces of Canada. The measurements were taken directly from the faces using standard tools like angle meter, measuring tapes, sliding, and spreading calipers. Table 3.1 shows the number of subjects for different age groups [11]:

The distribution of features by the six groups is shown in Table 3.2. Many measurements are paired, i.e., both the left side and the right side of the face have separate measurements, e.g., eye width, ear length, etc. Table 3.2 lists the paired and unpaired feature separately. While the data contained measurements of these features, not all the features had enough details for all statistical analyses. Some of the major head measurements include width of the head, width of forehead, height of head and nose, height of forehead, length of head, and circumference of head. Some of the face measurements are width of the face, height of the lower face, height of the chin, inclination of the profile, and general shape of the face. Orbits measurements include length of eye fissure, height of the orbit and height of the eye fissure. Nose measurements include width and height of the nose and major lips and mouth measurements include width of the mouth, height of the upper lip, height of the lower lip, tilt of the mouth and inclinations of lower and upper lips. Ear measurements examine the height and slant of the ear. All the measurements were taken by resting the head in normal position.

All measurements were aggregated and summarized by their mean and the variance. For each measurement in the face the data records the number of samples, mean value and the standard deviation for males and females separately. Furthermore, the statistics are recorded for people of different ages. Table 3.3 shows part of the measurements for width of the head.

3.2. Indirect measurements

The data obtained using direct measurements (referred as general data) are aggregated. This data does not support analyses that need individual measurements. Getting direct measurements from a large population is a tedious and time-consuming task. Many of the measurements can be indirectly obtained from photographs of the faces. Furthermore, standard collections of human faces are available.

We derive measurements from a set of standard face images using a graphical user interface (see Figure 3.1). While the interface is designed to capture the location of canonical points from both the frontal images as well as profiles, only frontal features are used in this research. The set of points captured via the interface is a subset of the feature points used by Farkas (see Table 3.4). A reference image showing the location of the feature and the test image is presented. The user is prompted to locate the corresponding feature in the test image. The user indicates the location of the feature by a mouse click. Figure 3.2 shows the location of the 29 feature points collected from a face.

Table 3.1. Age, gender, and population sample for North American Caucasians

<table>
<thead>
<tr>
<th>(A) Age group</th>
<th>(B) Number of subjects</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Males</td>
<td>Females</td>
<td></td>
</tr>
<tr>
<td>Birth-3 years</td>
<td>107</td>
<td>101</td>
<td></td>
</tr>
<tr>
<td>4–18 years</td>
<td>714</td>
<td>718</td>
<td></td>
</tr>
<tr>
<td>19–25 years</td>
<td>275</td>
<td>411</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.2. Distribution of features by categories

<table>
<thead>
<tr>
<th>Feature group</th>
<th>Unpaired features</th>
<th>Paired features</th>
<th>Total features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Head</td>
<td>13</td>
<td>4</td>
<td>17</td>
</tr>
<tr>
<td>Face</td>
<td>22</td>
<td>18</td>
<td>40</td>
</tr>
<tr>
<td>Orbits</td>
<td>2</td>
<td>38</td>
<td>40</td>
</tr>
<tr>
<td>Nose</td>
<td>19</td>
<td>18</td>
<td>37</td>
</tr>
<tr>
<td>Lips and mouth</td>
<td>14</td>
<td>8</td>
<td>22</td>
</tr>
<tr>
<td>Ears</td>
<td>0</td>
<td>38</td>
<td>38</td>
</tr>
</tbody>
</table>

Table 3.3. Width of the head (in mm)

<table>
<thead>
<tr>
<th>Age (in years)</th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Mean</td>
</tr>
<tr>
<td>0–5 months</td>
<td>8</td>
<td>110.1</td>
</tr>
<tr>
<td>6–12 months</td>
<td>20</td>
<td>118.8</td>
</tr>
<tr>
<td>1</td>
<td>18</td>
<td>125.5</td>
</tr>
<tr>
<td>2</td>
<td>30</td>
<td>130.5</td>
</tr>
<tr>
<td>18</td>
<td>52</td>
<td>151.1</td>
</tr>
<tr>
<td>19</td>
<td>109</td>
<td>151.1</td>
</tr>
</tbody>
</table>
The AR face database [12] was used to derive the feature points for individual faces. The database consists of images of 74 males and 58 females. The pictures were taken under controlled conditions. No particular restrictions were imposed on the participants. The face images were acquired with the subjects at approximately the same distance from the camera.

### 3.3. Data filtering

The direct measurement data (see Table 3.3 for an example) were reorganized to make certain aspects of the data more explicit and to remove some of the incomplete data. The changes are listed below:

- **Age adjustment:** The age of the group of subjects whose ages were between 0 and 5 months is specified as 0.25 years, ages between 6 and 15 months is specified as 0.75, while the ages from 19 to 25 is specified as 19.

- **Removal of derived data and missing data:** Derived data means that the measurement, although reported, is not actually measured directly. Instead it was indirectly computed from other direct measurements. Missing data simply means that a measurement is not reported. Since we are interested in using only measured data, the derived data and missing data are removed from our analysis.

- **Renaming of the feature names:** Some measurements in the data had left and right measurements. For instance, length of eye fissure (ex-en) has left and right entries. The input data are relabeled to ensure that all the feature names are unique.

### 4. Analysis of dimorphism

In this section, we analyze the aggregate and individual data assembled to determine sexual dimorphism in the human face. We use a statistical approach to answer some fundamental questions. Steps were taken to ensure that analysis is based on strong theoretical foundation and to avoid some pitfalls in data analysis. Some of the important considerations are to (a) ensure that the sample is the correct representation of the population, (b) use best measurement tools, (c) be cautious about multiple compari-
sons, and (d) make sure the graphs are accurate and reflect the data variation clearly.

For analyzing the input data, SAS/STAT statistical software is used [13]. SAS/STAT software, a component of the SAS (Statistically Analysis System), provides comprehensive statistical tools for a wide range of statistical analyses, including analysis of variance, regression, categorical data analysis, multivariate analysis, survival analysis, psychometric analysis, cluster analysis, and non-parametric analysis [13]. For our analysis, we used a mixture of SAS procedures and a set of utility software written in C++ to process the output and organize data.

Our analysis is organized around answering a set of fundamental questions about sexual dimorphism in the human face. These questions are:

1. Does sexual dimorphism exist in the human face? If it does, can this be quantified? (Section 4.1).
2. Does sexual dimorphism change as a function of age? (Section 4.2).
3. What features contribute the most towards dimorphism of the face? (Section 4.3).
4. How well can a face be correctly classified as a male or a female? (Section 4.4).

We use direct measurements to answer Questions 1 and 2. Since the direct measurements were in summary form, i.e., mean and standard deviation of a population, they were not suitable to answer Questions 3 and 4. Indirect measurements derived from images, provided feature values from individual faces and hence are suitable to understand the significance of individual features for both dimorphism analysis and for classification. Therefore, only the indirect measurements were used for solving the problems described by Questions 3 and 4.

4.1. Existence of dimorphism

Sexual dimorphism, though widely discussed in literature, has not been studied using formal analytical tools. In this section, we use statistical analysis to determine if dimorphism exists between male and female faces. The sexual dimorphism analysis and for classification. Therefore, only the indirect measurements were used for solving the problems described by Questions 3 and 4.

4.1.1. t-Test

If we have two datasets, each characterized by its mean, the standard deviation and the number of data points, we can use a t-test to determine whether the two means are distinct, if we assume that the underlying distributions to be normal. The two-sample t-test for independent samples is given by the following formulas:

\[
t = \frac{x_1 - x_2}{\sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}} \cdot \frac{1}{n_1} + \frac{1}{n_2}}
\]

In the above formula, \(x_1\) and \(x_2\) are the means of the males and females, \(n_1\) and \(n_2\) indicate the number of males and females respectively; \(s_1\) and \(s_2\) refer to the standard deviation of males and females. The values returned by the t-test represent estimates of statistical significance.

4.1.2. F-test

The F-test uses the F-statistic to test various statistical hypotheses about the variability of the distributions from which the sets of samples have been drawn. The F-statistic is the ratio of two estimates of population variances. The F-statistic tells if the variability of males is same as females. Along with t-test the F-statistic can be used to measure the degree of difference between two populations. In this case, the F-statistic is computed as:

\[
F = \frac{s_1^2}{s_2^2}
\]

where \(s_1^2\) and \(s_2^2\) are the variances of the two samples.

Table 4.1 summarizes the results of the t and F statistics for different feature groups. Due to the fact that we have a very large number of features, it is difficult to list all of them in a table. We have therefore, grouped them by the major groups as organized in face reconstruction literature [11]. A large t-value indicates significant difference in the feature between males and females and an F-statistic more than 2 implies a significant difference in the variability of the two populations. Thus the tables show that a large number of features are significantly different.

<table>
<thead>
<tr>
<th>Feature group</th>
<th>t-Statistic &lt;10 to 0</th>
<th>1 to 10</th>
<th>10 to 20</th>
<th>&gt; 20</th>
<th>F-statistic ≤ 1.0</th>
<th>1.0 to 1.5</th>
<th>1.5 to 2.0</th>
<th>≥ 2.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Head</td>
<td>4</td>
<td>6</td>
<td>5</td>
<td>—</td>
<td>1</td>
<td>12</td>
<td>2</td>
<td>—</td>
</tr>
<tr>
<td>Face</td>
<td>2</td>
<td>11</td>
<td>17</td>
<td>10</td>
<td>2</td>
<td>23</td>
<td>7</td>
<td>4</td>
</tr>
<tr>
<td>Orbits</td>
<td>8</td>
<td>20</td>
<td>5</td>
<td>1</td>
<td>4</td>
<td>17</td>
<td>9</td>
<td>4</td>
</tr>
<tr>
<td>Nose</td>
<td>11</td>
<td>14</td>
<td>12</td>
<td>—</td>
<td>8</td>
<td>18</td>
<td>3</td>
<td>8</td>
</tr>
<tr>
<td>Lips and mouth</td>
<td>4</td>
<td>6</td>
<td>11</td>
<td>—</td>
<td>—</td>
<td>16</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Ears</td>
<td>2</td>
<td>5</td>
<td>6</td>
<td>3</td>
<td>1</td>
<td>13</td>
<td>2</td>
<td>—</td>
</tr>
</tbody>
</table>
in males and females. For instance there are 12 features of the nose whose $t$-statistic is between 10 and 20 and 8 features whose $F$-statistic is greater than 2.

One feature that was significantly different is worth noting here. “Lower gnathion-aural surface distance,” i.e., the distance from bottom point of the ear (Point 17 in Figure 3.2) to the bottom point of the chin (Point 29 in Figure 3.2), stood out because of a large $t$-value (81.011). The value for this feature is as follows:

<table>
<thead>
<tr>
<th>Mean of males</th>
<th>Mean of females</th>
<th>$t$-value</th>
<th>$F$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>195.3</td>
<td>131.3</td>
<td>81.011</td>
<td>1.09595</td>
</tr>
</tbody>
</table>

This indicates that this feature is significantly larger in males than females, is fairly consistent ($F = 1.10$) and can be an important feature in an automated system to classify faces based on gender. In summary, the results of the $t$-test show that the mean values of the features of different parts of the face are significantly different from males to females. Furthermore, the results from the $F$-test indicate that the variability of the features is different among males and females.

### 4.2. Dimorphism as a function of age

It has been suggested that dimorphism in the human face can change as people grow [14]. Often it is difficult to determine the gender of newborn babies, but this task becomes easier as they grow older. How much of this task is dependent on other factors, e.g., facial hair in the case of males is not well understood. Our goal in this experiment was to determine if the features of the face show any changes in dimorphism as a function of age. To analyze this we use the aggregate data for those features that had measurements for populations of different ages. Only the features for which samples from newborn to adulthood are present were considered (128 out of 193 total features). Figure 4.1 shows how two features change over age.

In Figure 4.1 (left) the lower gnathion-aural distance, i.e., distance from bottom point of the ear to the bottom point of the chin on left side of the face is shown as a function of age. The graph shows that the feature is more prominent in males than in females and steadily grows with age in both males and females till the age of 15. After age 15, the feature becomes more stable for females, where as for males it shows a linear increase. This results in a wider gap between the values of males and females after age 15. The graph clearly shows that while the difference is not significant at age 1, it becomes quite significant by age 19.

Figure 4.1 (right) shows the changes in nasofrontal angle (angle between the bottom of the forehead and the start of the nose) and displays quite a different pattern. The graph does not show any structure in terms the relations between males and females. There is a steady growth in the feature value from age 5 to 15. From age 15 to 19, the feature is more significant in females than in males, but there is no strong pattern in the way the feature changes.

These two graphs are quite typical of the features we analyzed. Most graphs exhibited either a strong change after a certain age (as in Figure 4.1 (left)) or no strong pattern (as in Figure 4.1 (right)). Table 4.2 summarizes all the behavior of all the features as a function of age.

<table>
<thead>
<tr>
<th>Feature Group</th>
<th>Number of Features</th>
<th>Average Age of Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ears</td>
<td>35</td>
<td>13/14</td>
</tr>
<tr>
<td>Forehead</td>
<td>20</td>
<td>12</td>
</tr>
<tr>
<td>Others</td>
<td>73</td>
<td>15</td>
</tr>
</tbody>
</table>

Table 4.2 summarizes the number of features that change over age and the average age when the changes occur. It should again be noted, that since we have nearly two hundred features in the face, it is not efficient to list them individually. Instead, we organize them by feature groups as described earlier. Results show that dimorphism is not significant in young children but becomes increasingly significant as they age into adulthood. The age at which the SSD diverges in a large number of face features is around 13/14 around the age of puberty. Among different feature groups, the ears show the most changes.

### 4.3. Analysis of dimorphism

In Section 4.1, we demonstrated that the male and the female faces are significantly different. In this section, we describe attempt to determine which features and parts of the face are most responsible for the dimorphism. Individual dataset is the most appropriate and is used for this

![Figure 4.1. Value of an ear (left) and nose (right) feature as function of age.](image-url)
The table shows that there is a strong correlation between features in several groups: (a) orbits and nose and (b) orbits and lips. It is interesting to note that the correlation between features of the same group is not particularly high, except in the case of the ear. In the case of the ear, there are only two points in each ear for a total of 4 feature points. Since the ears are generally symmetric, the correlation is high. Some other correlations in the order of significance include nose-lips and mouth (79.0%), nose-nose (77.7%), face-nose (66.2%), face-lips and mouth (63.5%), face-face (58.3%), orbits-orbits (58.2%), face-ear (51.6%), and face-ears (45.9%). This indicates that face-ears features are less correlated when compared to other features. It should also be noted that features in different groups are more likely to be highly correlated than features in the same group.

4.3.2. Feature discrimination

The relative roles of different features and the feature groups can be determined in a variety of ways. We analyze this problem by using (a) step-wise discrimination and (b) principal component analysis.

4.3.2.1. Step-wise discriminant analysis. The step-wise discriminant analysis selects a subset of quantitative variables for discriminating among the classes. It initially computes separate F-statistic for each of the variables and then selects the variable with largest F-statistic. Each variable is tested for retention in the discriminant function based on its association with other variables, and the process is repeated until all the variables meeting the levels of significance are considered. At each step the goal is improve the overall recognition rate.

The first 10 steps of step-wise discriminant analysis are shown in Table 4.4. It lists the most significant features, F-statistic for the features, and the average canonical correlation. The table shows that the first variable contributes around 46% towards the discrimination of male and female faces. As we reach the end of the table, we observe that all 10 variables listed in the table are able to explain around 77% of the differences of the faces of males and females. Figure 4.2 shows the most important features identified by step-wise discriminant analysis.

To understand the roles of features, we further analyze the top 18 distances. Each distance corresponds to a pair of feature points in the face. Each point in turn belongs to certain part of the face, e.g., orbits, nose, or ear. Thus a distance feature (e.g., those shown in Figure 4.2) can either be classified as within a feature group (e.g., orbit-orbit) or across two feature groups (orbit-nose).

From the variables obtained from step-wise discriminant analysis, we determine if the variables represent features from same feature group (head-head, face-face etc.) i.e., within the feature or features from different feature group (head-face, face-nose etc.) i.e., across the feature.

---

1 As noted before the set of features in the individual dataset is not identical to the aggregate dataset (used in Sections 4.1 and 4.2).
The percentage contribution of each of the feature groups (head, face, nose, lips and mouth, orbits, and ear) for discriminating among the classes is shown in Table 4.5. The table indicates that face features contribute the maximum (38.8%), while the nose and head features contribute least (5.6%) towards sexual dimorphism in the face. It is also interesting to note that the most significant feature in terms of dimorphism (Section 4.1), the lower gnathion-aural surface distance (the distance from bottom point of the ear, i.e., Point 17 to the bottom point of the chin, i.e., Point 29) is not deemed to be among the most significant in step-wise discriminant analysis. The reason for this is that the distance is derived from direct measurements (i.e., on the 3D face surface of an actual person), while the distances used for analysis in this section are based on indirect measurements, which are based on the projection of the face onto a 2D image. It is interesting however, that the distance from the top of the left ear to the bottom of the chin is deemed significant in this analysis. This suggests that the distance from the ear to the chin plays a significant role in the face dimorphism.

4.3.2.2. Principal component analysis. Another way to view the role of the features in the dimorphism process is to use the principal component analysis (PCA). As we have noted, we have 29 feature points resulting in 406 distance features. Not all of them can be equally responsible for face discrimination between males and females. Principal component analysis is a multivariate technique for examining relationships among several quantitative variables [13]. The analysis generates eigenvalues, eigenvectors, and standardized or unstandardized principal component scores from a set of measurements [16]. It should be noted that principal component analysis does not show which features are most useful for recognition. It is a method to reduce the dimensionality of the space. Our goal in using it here to examine what is the minimum dimension of this feature space.

The intuitive notion of principal components is that if we have a set of multivariate measurements, a set of independent vectors (eigenvectors) can be used to describe them. The eigenvalue of the corresponding eigenvector indicates its importance in the blending process. Thus the top eigenvectors can be used to concisely describe the sample population to a specific degree.

The results show that the first principal component explains about 50% of the total variance, and the top 10 principal components are able to explain about 83% of the variance in the dataset.

Since each principal component has 406 elements, detailed analysis of all the components is difficult to make and interpret. To get additional understanding into the nature of features responsible for sexual dimorphism, we also applied PCA to the male and female faces separately. We then selected the top ten weights in each eigenvector and analyzed the corresponding feature groups. Finally,
we determined the contribution of each feature group towards the feature discrimination based on principal component analysis. The same procedure is followed for individual male and individual female dataset. The percentage contribution for each feature when males and females are considered separately and when considered together is provided in Table 4.6.

Table 4.6 shows that the face feature group contributes a lot in dimorphism (32.8%) when compared to other feature groups. This is true both when males and females are considered separately and together. Also, when independent males and female datasets are considered, lips and mouth (26.0%, 30.0%) play a major role in recognizing, followed by orbits (18.3%) among males and ears (14.3%) in females.

It is not possible to list all the features in each feature group. The most important ones include the highest and lowest points of the ear (ear group), the most lateral points on side of nose (nose group), the point on the hairline in the midline of the forehead (head group), the mid point of chin and the most prominent lateral points on right and left side of the skull (face group), the midpoint on upper lip, the left and right most points of closed lip (lips and mouth group) and the inside and outside points of the eyes and the highest points on the eyebrow (Orbits group).

4.4. Face classification based on features

Step-wise discrimination and principal component analysis indicate that a small number of features can adequately explain the differences in the faces of men and women. Our goal in this experiment was to determine how well we could expect to perform the task of face discrimination based on gender, by using these features. Step-wise discriminant analysis gave us indications of which features are more important. Table 4.4, lists these features in decreasing order of importance.

Discriminant analysis is used to determine a discriminant criterion to classify each observation into male and female groups. The derived discriminant criterion is then used to estimate the error rates (probabilities of misclassification). Table 4.7 gives an overview of the percentages of correct classification and error rates when we use the distance features obtained from the step-wise discrimination analysis. The first row of the table indicates the correct classification and error rates when only one distance (obtained from step-wise discrimination analysis) is considered. The second row corresponds to the correct classification and error rates when two distances (first and second) are considered. The procedure is continued till all the distances obtained from step-wise discrimination analysis are considered. Figure 4.3 shows the graphical representation of Table 4.7, with error rate in y-axis and steps in x-axis.
The graph indicates a general steady decrease in the error rate as the number of variables increase until Step 6. After that error rate shows some variations but does not change significantly. The error rate is the minimum when all the variables are considered (3.5%), while it is the maximum when only one variable is considered (15.6%). For 96% correct classification, the minimum number of features we need to consider is 8.

4.5. Summary of analysis

In summary the following conclusions can be made from the above analysis.

1. Sexual dimorphism is strongly demonstrated in the human face. Section 4.1 showed that around 85% of features show significant difference in male and female features.
2. SSD of the face changes over time. Section 4.2 showed that around 57% of face features show this pattern of change. The average age at which the sexual dimorphism becomes more significant is around 13.
3. The correlation between different feature groups of the face is demonstrated in Section 4.3. It is observed that correlation between same feature groups is not particularly high except in the case of ears. A relatively small number of features can describe a significant difference in SSD. While there are 406 features in the analysis, around 89% of the difference can be explained by 18-20 features. Also, the results indicated that face features contribute the maximum, while nose and head features contribute the least towards sexual dimorphism of the face.
4. It is possible to obtain a high (male/female) classification rate of 96% correct classification using 18-20 features.

5. Summary and future work

Sexual dimorphism is prominent among different mammals, insects, and other species. In most of the species the dimorphism is in size. The focus of this work is to study sexual dimorphism in the human face using quantitative methods. Our study differs from previous studies by additional breadth and depth of analysis of sexual dimorphism in the face. Statistical methods are used to confirm that sexual dimorphism is strong and widespread among face features. Furthermore, the degree of dimorphism changes as a function age. Our analysis shows that SSD is low for young children and becomes more prominent in the face around age 13 with about 57% of the face features showing changes in SSD as a function of age. Additional analyses show that there is some degree of correlation between features in the face, but not uniform across different features. The step-wise discriminant analysis showed that face features contribute the most (38.8%), while the nose and head features contribute least (5.5%) towards sexual dimorphism in the face. Principal component analysis indicated that face and orbit features contribute more towards dimorphism in comparison to other features.

This study can be extended in many different directions. The study relied on only the distance measures for studying dimorphism. Ratios have been proposed as a mechanism to provide compact descriptions for human face [16]. The same quantitative approaches can be used to include ratios too for future study. Using ratios achieves a degree of normalization of dimensions. We expect the results on ratios to be similar to the results presented here. Researchers have studied human faces with appropriate dimensions and ratios for making paintings and portals. It should be noted that the number of possible ratios is very large. For the datasets used in this study, the number of distances is 406 (26C2) and hence the total number of possible ratios will be 406C2. The set of independent ratios must be determined and perhaps further pruned for effective analysis. All the measurements (both direct and indirect) were conducted on North American Caucasian populations. This can be extended to other races as well to determine the features responsible for differences among them.

The results from this study can be used to assist automated systems for gender classification based on face. Reliable extraction of features is central to success of this approach. The positive aspect of this study is that there are a lot of features that are quite distinct in males and females; hence a relatively small number of measurements may suffice for this purpose.

References


