

# Eigenface and SIFT For Gender Classification

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## استخدام الإيجن فيس و أس آي أف تي في عملية تصنيف الجنس

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### الخلاصة:

في هذا البحث تمت دراسة خمس طرق لتصنيف الجنس (ذكر أو أنثى) وتحليلها، الغرض من تلك الطرق الخمس هو الحصول على الصفات الأساسية من صورة الوجه ومن ثم استخدام تلك الصفات بوصفها مدخلات للمصنف "ماكينة المتجه المسند" SVM. في الطريقة الأولى، تم اعتماد صفات تحليل المكونات الأساسية PCA بوصفها مدخلات الى المصنف SVM. في الطريقة الثانية، فإن نتائج تطبيق طريقة الخصائص ثابتة القياس SIFT Scale Invariant Features Transform يتم استخدامها بوصفها مدخلات في المصنف SVM. في الطريقة الثالثة، يتم اعتماد مخرجات الإيجن فيس Eigenfaces بوصفها مدخلات الى طريقة الخصائص ثابتة القياس ومن ثم استخدام مخرجاتها بوصفها مدخلات الى المصنف SVM. في الطريقة الرابعة، يتم استخدام مخرجات الإيجن فيس بوصفها مدخلات الى VSIFT ومن ثم تصنيفها بوساطة المصنف SVM. واخيرا في هذا البحث تم تطوير طريقة VSIFT وادخال مخرجات هذه الطريقة الى المصنف SVM. إن نتائج التنفيذ العملي للطريقة المفترضة هذه تبين انها ذات كفاءة عالية في عملية التصنيف مقارنة مع الطرق الأربعة الأخرى. لقد تم الحصول على صور الوجوه المستخدمة في عملية التدريب والاختبار من موقع مشاريع بحث علم بصريات الحاسوب (CVSRP). إن الهدف من البحث هو حساب نتائج تطبيق استخدام الإيجن فيس في الطريقة المفترضة والجديدة في تحديث VSIFT لتصنيف الوجوه الى ذكر أو أنثى، وكذلك تحليل أداء الطريقة الجديدة ومناقشتها.

### Abstract

In this paper, we study and analyze five different approaches for gender classification (Male or Female). The purpose of approaches is to extract the main features from face image and for each approach; we used these features as input to the Support Vector Machine SVM classifier for classification process. In the first approach, we implemented the Principal Component Analysis PCA features as input to the SVM classifier. In the second approach, the resulted parameters of Scale Invariant Features Transform approach are used as input to SVM classifier. In the third approach, we implemented Eigenfaces as input to SIFT, and then the results of SIFT are used as input to SVM classifier also. In the fourth approach, we implemented Eigenfaces to be input to Volume-SIFT (VSIFT) and then used as input to SVM classifier. The last, we modified the VSIFT approach and use as input to SVM classifier. The practical implementation results show that the

proposed approach (modified VSIFT) gave us high performance of gender classification than other approaches.

The training and testing images set consist of number of faces which are obtained from (Computer Vision Science Research Projects).

The aim of this paper is to analyze and discuss the results of applying the eigenfaces into the new proposed approach of modifying Volume-SIFT for classifying the faces into its gender.

Key words: Face classification, PCA, Eigenface, SIFT, Face recognition, Feature Extraction.

## **Introduction**

Gender classification problem has a high application potential in some places where people should be served depend on their gender, such as a costumer statistics collection in special places like park places, supermarkets, restaurants and also security surveillance in building entrances. Hence, it is an important problem in computer aided systems which interact with human being.

This paper focuses on classification of face images according to their gender using several approaches of features classification, **one of them** is Principal Component Analysis PCA. PCA [1] is an information-preserving statistical method used for dimensionality reduction and feature extraction. It is based on auto-associative memories paradigm, where input is associated to itself. It is primarily used for determining an orthogonal space with minimal dimension for representing the sample data. In other words, it is a linear transformation of sample of points in N-dimensional space, for exhibiting the properties of the sample most clearly along coordinate axes. The sample variances are extreme and uncorrelated along the new axes. So, by definition, PCA can show linear interdependence in data. This approach, (PCA), we used PCA algorithm to convert the input image into smaller space size and used it as input to Support Vector Machine SVM classifier to get gender class.

Dr. P. K. Suri et al. have proposed a combined approach for face detection and gender detection, where they have used the concept of principal component analysis. The crux of the work lies in the mathematical formulation of mean square error since it will give us the indication for the female or male candidates' face, hence gender detection [2].

The **second approach**, the Scale Invariant Features Transform SIFT has been applied in gender classification task. This approach extracts blob-like shape local features from an image, and represents each blob structure at the appropriate scale with explicit mechanism of automatic scale selection [3]. Then clustering those local features by Hough transform.

Morteza et al. [4] proposed a robust approach for face detection and gender classification in color images, the approach based on mathematical analysis is represented in three stages that eliminates alignments step. First, a new color based face detection method is preserved with a better result and more robustness in

complex backgrounds. Next, the features which are invariant to affine transformations are extracted from each face using scale invariant features transform (SIFT) method, and employing a SVM classifier on a database of face images. The **third approach**, converts each image's face (training and testing faces) into eigenface, and applies it to SIFT algorithm to get local features and classifying. The **fourth approach**, applies eigenface to Volume-SIFT algorithm to get local features that were used in the classification process. The **last (and proposed) approach**, reducing factor ratio between octaves. All those approaches are evaluated practically and the results are shown.

Section 2 explains the mathematics of PCA, section 3 discusses the concept of SIFT, sections 4 ,5 discussed the Volume-SIFT approach and the proposed approach respectively,. Section 6 discusses the implementation and results of the three algorithms. Section 7 shows the final conclusion about the results of the implementation for the five gender classification approaches.

### Principal Component Analysis (PCA) approach

The Principal Component Analysis (PCA) is a statistical analysis method and one of the most successful techniques that have been used in image recognition and compression.

By mathematical statistics, the eigenvectors of the covariance matrix of the face image set will be translated to a vector in a very high dimensional space. The variations among to the face images will be ordered in the eigenvector. On the other hand, the eigenvector is a principal component set of features that commonly characterizes the variation among original face images, called eigenface [5].

The mathematical steps of PCA are shown as the following [5, 6, 7]:

Let a face image  $R$  be a 2-dimension  $K$  by  $K$  array of intensity values. Convert each  $R$  of size  $(K * K)$  into  $I$  vector of size  $(K^2 * 1)$

The training face image are  $I_1, I_2, \dots, I_N$ . The average (mean) face of the set is defined as  $\bar{I}$  :

$$\bar{I} = \frac{1}{N} \sum_{i=1}^N I_i, \text{ where } N \text{ is the number of training faces.}$$

Each face differs from  $\bar{I}$  is

$$\phi_i = I_i - \bar{I}, \quad \text{where } i = 1, \dots, N, \text{ , } (k^2 * 1 \text{ vector})$$

The face differs vector  $A$  of  $\phi_i$  is

$$A = [\phi_1 \phi_2 \dots \phi_N], \text{ (} K^2 * N \text{ Matrix)}$$

And then the large vector set is subject to principal component analysis which seeks a set of  $N$  orthogonal vectors  $\mu_i$ .

The  $k^{th}$  vector,  $\mu_k$ , is chosen such that

$$\lambda_k = \frac{1}{N} \sum_{i=1}^N (\mu_k^T \phi_i)^2$$

Is a maximum, subject to

$$\mu_k \mu_l^T = \delta_{kl} = \begin{cases} 1, & \text{if } l=k \\ 0, & \text{otherwise} \end{cases}$$

The vector  $\mu_k$  and scalars  $\lambda_k$  are the eigenvectors and eigenvalues, respectively, of the co-variance matrix  $C$ .

$$C = \frac{1}{N} \sum_{i=1}^N \phi_i \phi_i^T = AA^T, \text{ where } i = 1, \dots, N$$

$C$  is a  $K^2$  by  $K^2$  matrix (very large matrix and not practical) and its eigenvectors and eigenvalues are  $K^2$ .

To overcome this problem, we must reduce the intractable computation; we solve the  $K^2$  dimensional eigenvectors in this case by first solving for the eigenvectors of  $N$  by  $N$  matrix, and then taking the appropriate linear combinations of the face images  $\phi_i$ . Consider the eigenvectors  $v^i$  of  $A^T A$  such that

$$A^T A v_i = \mu_i v_i$$

Pre-multiplying  $A$ , and then we get

$$A A^T A v_i = \mu_i A v_i$$

where  $A v_i$  is the eigenvectors of  $C = A^T A$ .

Consider the  $N$  by  $N$  matrix  $L$

$$L = A^T A, \text{ where } L_{MN} = \phi_M^T \phi_N$$

And find the  $N$  eigenvectors  $v_i$  of  $L$ .

These vectors determine the linear combinations of the  $N$  training set face images to form the eigenfaces  $\mu_l$ .

$$\mu_l = \sum_{k=1}^N \phi_k v_{lk}, \text{ where } l=1, \dots, N.$$

The calculations from  $K^2$  to the number of the face images  $N$ . in practice,  $N \ll K^2$ . from the above analysis, we find that the calculation is greatly reduced.

By using the eigenfaces vectors,

$$\mu_i, \text{ where } i = 1, 2, \dots, N,$$

we can project the images of faces  $I_1, I_2, \dots, I_N$  into a new sub space of faces images  $W$  matrix ( $N * N$ ) as follow:

$$W = [w_1 w_2 \dots w_N] = \mu^T \phi$$

### Scale Invariant Feature Transform (SIFT) approach

SIFT is a method for extracting distinctive invariant features from images that can be used to perform reliable matching between different views of an object or scene. The features are invariant to image scale and rotation, and provide robust matching across a substantial range of affine distortion, change in 3D viewpoint, addition of noise, and change in illumination. The features are highly distinctive,

in the sense that a single feature can be correctly matched with high probability against a large database of features from many images. The recognition proceeds by matching individual features to a database of features from known objects using a fast nearest-neighbor algorithm, followed by a Hough transform to identify clusters belonging to a single object, and finally performing verification through least-squares solution for consistent pose parameters [8].

SIFT transforms an image into a large collection of local feature vectors, each of these features is invariant to image scale, rotation and transformation. It consists of four major stages: [8, 9, 10]

**Scale-space extrema detection:** A difference of Gaussian function is applied to identify potential interest points that are invariant to scale and rotation.

**Keypoint Localization:** At each candidate location, a detailed model is fit to determine location and scale. Keypoints are selected based on measures of their stability.

**Orientation assignment:** One or more orientations are assigned to each keypoint location based on local image gradient directions.

**Keypoint descriptor:** The local image gradients are measured at the selected scale in the region around each keypoint. These are transformed into a representation that allows for significant levels of local shape distortion and change in illumination.

This approach generates a feature vector of length 128 for each feature point or keypoint location. An important aspect of this approach is that it generates large numbers of features that densely cover the image over the full range of scales and locations.

However, many features from an image will not have any correct match in the training database because they arise from background clutter or were not detected in the training images. Therefore, it would be useful to have a way to discard features that do not have any good match to the database. A global threshold on distance to the closest feature does not perform well, as some descriptors are much more discriminative than others. A more effective measure is obtained by comparing the distance of the closest neighbor to that of the second closest neighbor. If there are multiple training images of the same object, then we define the second-closest neighbor as being the closest neighbor that is known to come from a different object than the first, such as by only using images known to contain different objects. This measure performs well because correct matches need to have the closest neighbor significantly closer than the closest incorrect match to achieve reliable matching. For false matches, there will likely be a number of other false matches within similar distances due to the high dimensionality of the feature space. We can think of the second-closest match as providing an estimate of the density of false matches within this portion of the feature space and at the same time identifying specific instances of feature ambiguity.

David [8] has used an approximate algorithm, called the Best-Bin-First (BBF) algorithm. This is approximation in the sense that it returns the closest neighbor with high probability. The BBF algorithm uses a modified search ordering for the k-d tree algorithm so that bins in features space are searched in the order of their closest distance from the query location.

To maximize the performance of object recognition for small or highly occluded objects, identifying objects with the fewest possible number of feature matches. The reliable recognition is possible with as few as 3 features. A typical image contains 2,000 or more features which may come from many different objects as well as background clutter. Fortunately, much better performance can be obtained by clustering features in pose space using the Hough transform.

The Hough transform identifies clusters of features with a consistent interpretation by using each feature to vote for all object poses that are consistent with the feature. When clusters of features are found to vote for the same pose of an object, the probability of the interpretation being correct is much higher than for any single feature. Each of our keypoints specifies 4 parameters: 2D location, scale, and orientation, and each matched keypoint in the database has a record of the keypoint's parameters relative to the training image in which it was found. Therefore, we can create a Hough transform entry predicting the model location, orientation, and scale from the match hypothesis. This prediction has large error bounds, as the similarity transform implied by these 4 parameters is only an approximation to the full 6 degree-of-freedom pose space for a 3D object and also does not account for any non-rigid deformations. Therefore, we use broad bin sizes of 30 degrees for orientation, a factor of 2 for scale, and 0.25 times the maximum projected training image dimension (using the predicted scale) for location. To avoid the problem of boundary effects in bin assignment, each keypoint match votes for the 2 closest bins in each dimension, giving a total of 16 entries for each hypothesis and further broadening the pose range.

### **Volume-SIFT approach**

Even though there have been a few studies using SIFT for face recognition, they simply applied the core SIFT algorithm. It is known that SIFT was designed for general object recognition/detection. General objects are rigid, and there are sharp transitions between different sides. However, faces are non-rigid and smooth. Hence, the original SIFT approach may not be optimal for face recognition applications.

Cong et al. [3] proposed new approach called Volume-SIFT to remove unreliable keypoints detected by standard SIFT algorithm. The process performed by eliminating unreliable keypoints not based on the contrast at the location of each candidate keypoint but based on the volume of the sigma (scale) of the keypoint. Therefore, the keypoint will be removed if the volume sigma (result of multiplying the Difference of Gaussian by the scale of that level) is below some threshold.

## New ratio of Octaves (modified threshold) approach

The key locations in scale space are identified by looking for locations that are maxima or minima of difference-of-Gaussian function. This process performed by resizing the dimensions of image into smaller size, and each level is called Octave, and in each octave Difference-of-Gaussian (DoG) is performed using ratio called Sigma which is used for scaling the blurring the re-sampled images (number of intervals).

David [8] experimentally, shows that the best value of resizing image (ratio of octave) is 0.5 in the object recognition, but this ratio not gave us a best result and we experimentally found the best ratio is 0.75, and we get best results as shown in implementation and results section.

## Practical Implementation and Results

In this section, we present and discuss each of the classification approach in detail. The database of faces is obtained from (Computer Vision Science Research Projects), and it contains different faces with varying lighting, poses and facial expressions.

### 6-1 Database of Faces

Computer Vision Science Research Projects (CVSRP) provides us many images of faces (males and females). We used up to 400 images of faces for training process (200 images for females and 200 images for males), and for each gender there exists 20 images of different poses and conditions (therefore, 10 male persons and 10 female persons are used for training set). We used 200 images of faces for testing process (100 images for females and 100 images for males). Figure (1) shows examples of training and testing faces of both genders.

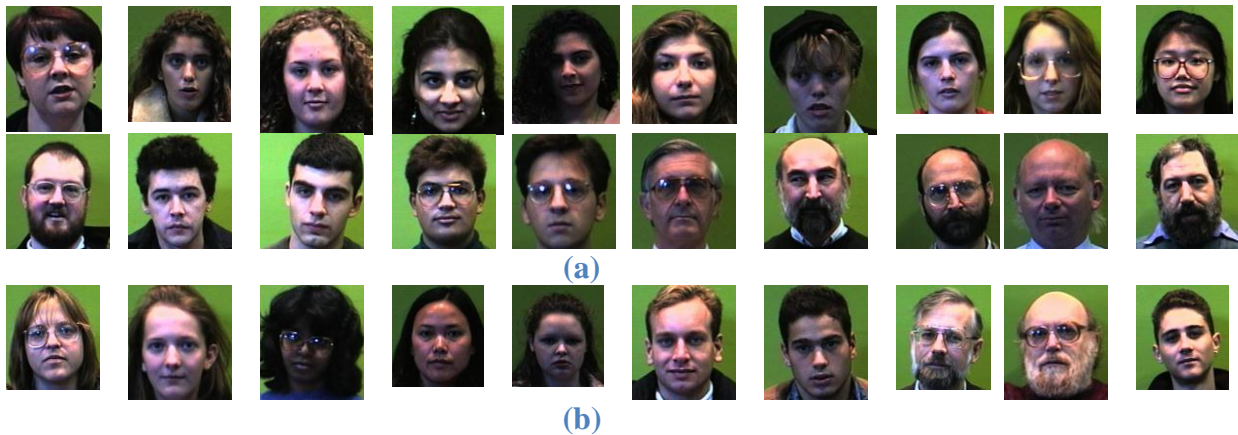


Figure (1) a) examples of faces which are used in the training set b) examples of faces which are used in the testing set.

## 6-2 Algorithms

### 1) PCA Algorithm:

**Input:**  $X_{i,j} = \{x_1, x_2, \dots, x_m\}$ ,  $i=1, 2, \dots, M$ ,  $j=1, 2, \dots, N$ .

where  $X$  is a matrix of  $(M*N)$ ,  $M$  is number of face samples (Males and Females), and  $N$  is number of pixels of image vector  $x$ .

**Begin:**  $Mean\_X$  is vector of  $(1*M)$ , each element of  $Mean\_X$  is the average of corresponding column of  $X$  matrix.

$Sub\_X$  is matrix of  $(M*N)$ , each row represents the centered zero mean of faces vectors, and calculated as follow:

For each  $i^{th}$  row of  $X$

$$Sub\_X_{i,j} = X_{i,j} - Mean\_X_j, \text{ for } j=1, 2, \dots, N.$$

Calculate covariance matrix of  $Sub\_X$ :

$$X\_Cov = Sub\_X * Sub\_X^T, \text{ and size of } X\_Cov \text{ is } (M*M)$$

Calculate Eigenvectors  $First\_Eig\_X_{i,j}$  of  $X\_Cov$ , for  $i=j=1, 2, \dots, M$ .

Where  $M$  is the number of sample images.

Get first max  $K$  Eigenvectors ( $Eig\_X_{i,j}$ ) of covariance matrix of  $Sub\_X^T * Sub\_X$  by the following:

$$Eig\_X_{i,j} = Sub\_mean_{j,i} * First\_Eig\_X_{i,j}, \text{ for } i=1, 2, \dots, N, j=1, 2, \dots, K.$$

Where  $N$  is the number of source image pixels, and  $K$  is the number of eigenvectors and  $K \leq M$ .

**Output:** the output is  $Eig\_X$  matrix, used to project the  $Sub\_X$  into new reduced dimensions  $New\_X_{i,j}$ , where  $i=1, 2, 3, \dots, M$ ,  $j=1, 2, \dots, K$ . by applying the following:

$$New\_X_{i,j} = Sub\_X_{i,j} * Eig\_X_{j,j}, \text{ for } i=1, 2, \dots, M, j=1, 2, \dots, N$$

Where  $M$  is the number of trained faces samples, and  $N$  is the number of image pixels.

The classification process performed by converting image of face into new space and using Support Vector Machine SVM to classify the input image of face into its corresponding gender.

### 2) SIFT Algorithm:

**Step 1: Input:**  $X$  is input image.

**Step 2: Initialization:** Octaves = 4 ; Intervals = 5;  $\delta = 2^{1/2}$  ; Scale\_Size = 0.5; Contrast\_Threshold = 0.02 ; Curvature\_threshold = 10.0

**Step 3: Begin:**

**Step 4: For** Octave= 1 To Octaves

**Step 5: For** Interval = 1 To Intervals

**Step 6:**  $G(x, y, \delta) = \frac{1}{2\pi\delta^2} e^{-(x^2+y^2)/2\delta^2}$



**Step 7:** Find  $C = \text{Convolution } X \text{ with } G$  ; where  $G$  is a Gaussian filter and  $C$  is a blurred image.

**Step 8:**  $\delta = \delta^{1/2}$

**End for Interval**

**Step 9:** Find Difference of Gaussian (DoG) between each two adjacent of Intervals of  $C$ .

**Step 10:** Find the **Extrema** (Maximum and Minimum value of **DoG**) for each point in the **DoG**.

**Step 11:** **Pos** = coordinates of **Extrema** when **DOG** is above **Contrast\_threshold**

**Step 12:** Eliminates all points **Pos** that have value of **DoG** Below **Curvature\_threshold**

**Step 13:** **Orient** = The orientations of key-points (**Pos**)

**Step 14:** **Scale** = The scale of key-points (**Pos**)

**Step 15:** **Desc** = Extract feature descriptors for the key-points.

Where the descriptors are a grid of gradient orientation histograms, and the sampling grid for the histograms is rotated to the main orientation of each key-point

**Step 16:** Resize the **X** image by **Scale\_size** ratio

**End for Octave**

**Step 17: Output:** **Pos**: vector ( $N*1$ ) contains at coordinates of  $N$  key-points.

**Step 18: Scale:** vector ( $N*1$ ) contains at scale of each point.

**Step 19: Orient:** vector ( $N*1$ ) contains at orientation of each point.

**Step 20: Desc:** matrix ( $N*128$ ) matrix with rows containing the feature descriptors corresponding to the  $N$  key-points.

### 3) Eigenface and SIFT Algorithm:

**Step 1: Input:**  $New\_X$  is eigenfaces matrix of  $X$  image, produced by  $Sub\_X * Eig\_X$ , depending on the output of PCA algorithm.

**Step 2: Initialization:** The same step of SIFT algorithm.

**Step 3: Begin:**

...

The same steps (3-16) of SIFT.

...

**Step 17: Output:** the same steps (17-20) of the SIFT algorithm.

### 4) Volume-SIFT Algorithm:

**Step 1: Input:**  $New\_X$  is eigenfaces matrix of  $X$  image, produced by  $Sub\_X * Eig\_X$ , depending on the output of PCA algorithm.

**Step 2: Initialization:** The same step of SIFT algorithm.

**Step 3: Begin:**

...

The same steps (3-16) of **SIFT algorithm** but change only the **Step 11** with the following:-

**Step 11: Pos** = coordinates of **Extrema** when **DOG** is above **Contrast\_threshold**

...

**Step 17: Output:** the same steps (17-20) of the SIFT algorithm.

#### 5) New Proposed approach Algorithm:

**Step 1: Input:** *New\_X* is eigenfaces matrix of **X** image.

**Step 2: Initialization:** The same steps of **Volume-SIFT** algorithm but change only the following:

**Scale\_Size** = 0.75

**Step 3: Begin:**

...

The same steps (3-16) of **Volume-SIFT** algorithm.

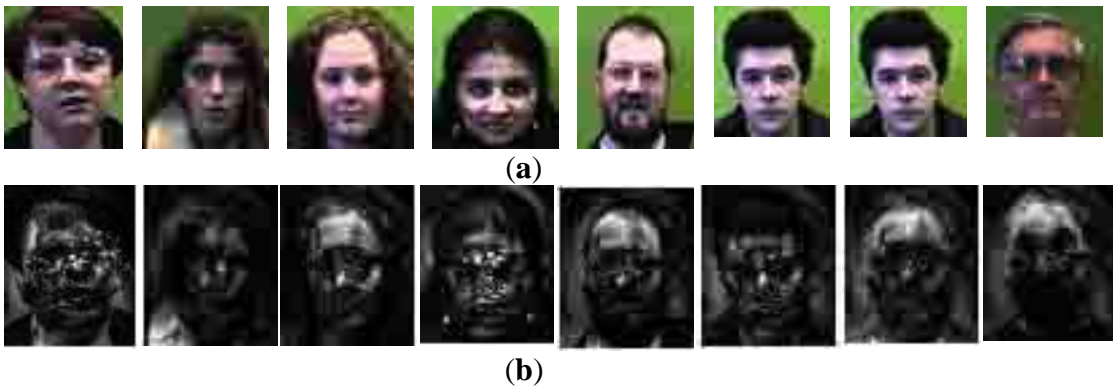
...

**Step 17: Output:** the same steps (17-20) of the **Volume-SIFT** algorithm.

### 6-3 Results

#### PCA Approach

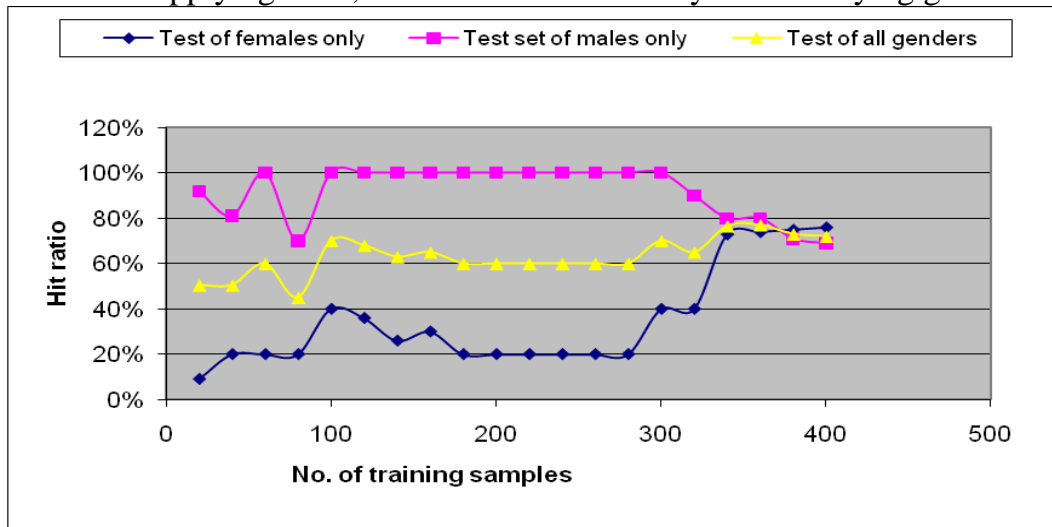
Figure (2) show samples of images which are used to produce eigenfaces by applying PCA algorithm, where figure (2-a) shows the original images of faces, and figure (2-b) shows the eigenfaces of original images which are produced by PCA algorithm.



**Figure (2) a) samples of training set of faces b) the corresponding eigenfaces of these images**

To classify image face into its corresponding gender, we used SVM classifier, Figure (3) illustrates the performance of PCA algorithm when it was implemented at different number of training images. The yellow line represents the ratio of implementation when the test samples involved both types of gender (Female and Male) together, and the chart illustrates the performance of algorithm arrived at good ratio (between 70%), and still so when the number of training images are

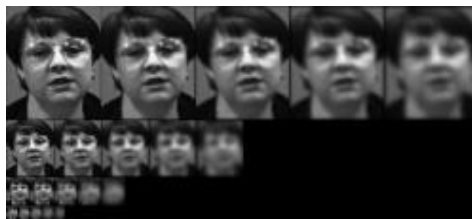
above than 320 training images. The performance of using new space, which was resulted from applying PCA, arrived to 72% accuracy for classifying gender class.



**Figure (3) performance of PCA algorithm in the classifying the faces into their corresponding gender at different number of training samples**

### SIFT Approach

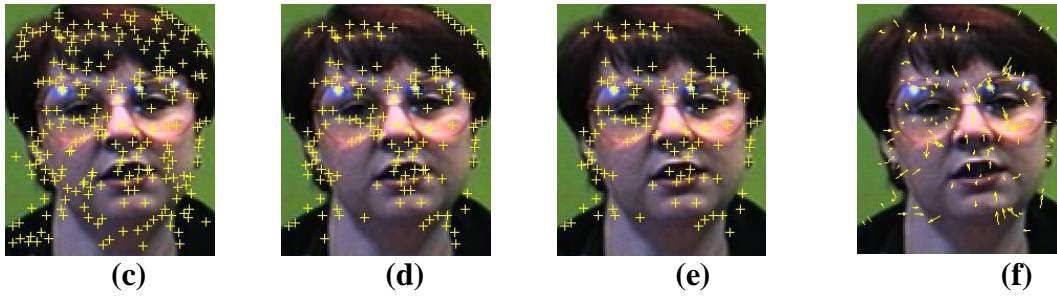
To get Key-points there are several tasks happened to the face image during the implementation of SIFT approach. Figure (4) illustrates the steps of SIFT processing for achieving key-points of particular face image, figure (4-a) shows the pyramid of implementing the Gaussian filter on the images (four octaves, and five intervals for each octave), figure (4-b) shows the pyramid of Different of Gaussian (DoG), figure (4-c) shows the locations of selected key-points before removing unnecessary points and the number of key-points are 227 points, figure (4-d) shows the locations of key-points (remain 142 points) after removing the location which have DoG value below than contrast threshold, figure (4-e) shows the locations of key-points (remain 115 points) after removing the locations which have DoG value above than curvature threshold, and the last figure (4-f) illustrates the final result of SIFT implementation, which shows the points with their scales and orientations.



(a)

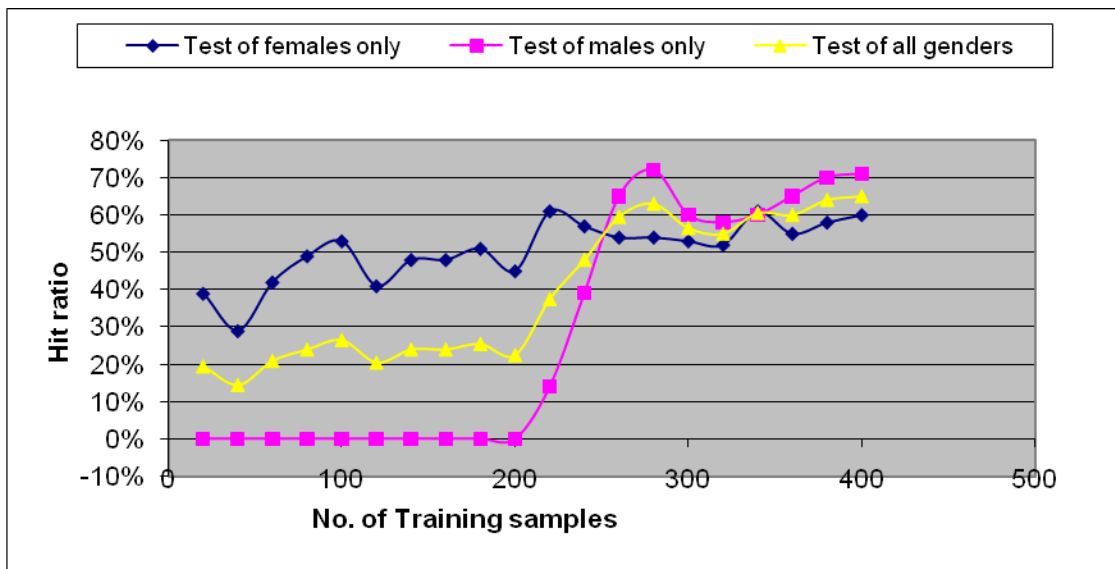


(b)



**Figure (4) Tasks of implementing the SIFT procedure, a) Pyramid of Gaussian filter of images, b) Pyramid of DoG, c) Locations of selected key-points before removing unnecessary points, d) Locations of selected key-points after applying contrast threshold, e) Locations of selected key-points after applying curvature threshold, f)Result of SIFT procedure, resulted key-points, scale, and orientation.**

The classification of input face image performed by calculating SIFT key-points of input face image and using Hough transform clustering to get the nearest points that satisfy the matching between the features of input image (SIFT Points) and features of trained database (SIFT key-points of training faces images). Figure (5) shows the implementation of classifying face gender by using SIFT key-points with different number of training faces images for both genders (males and females), where the blue, red, and yellow lines represent hit ration of implementing the classification using females only , males only, and both genders respectively.



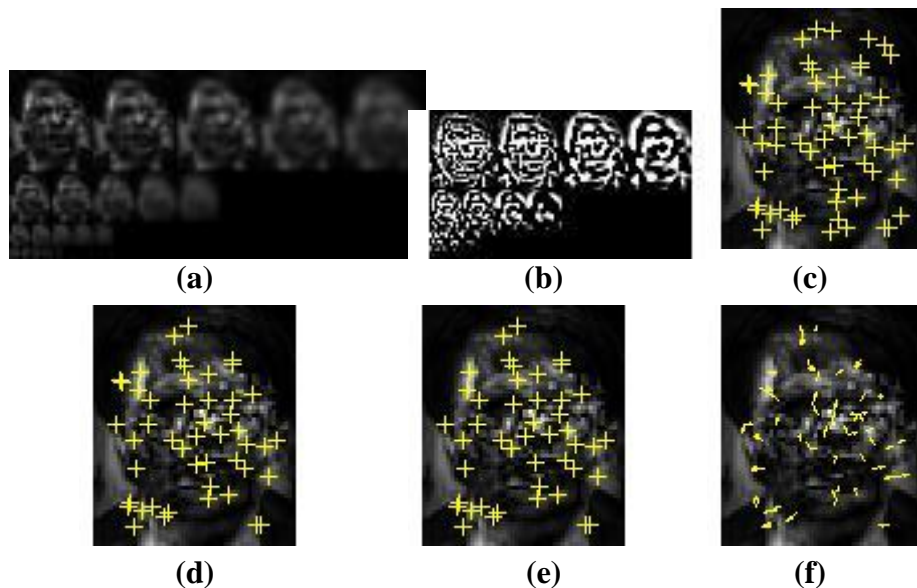
**Figure (5) performance of classifying faces to their corresponding gender using SIFT key-points at different number of training faces images.**

### Eigenface and SIFT approach

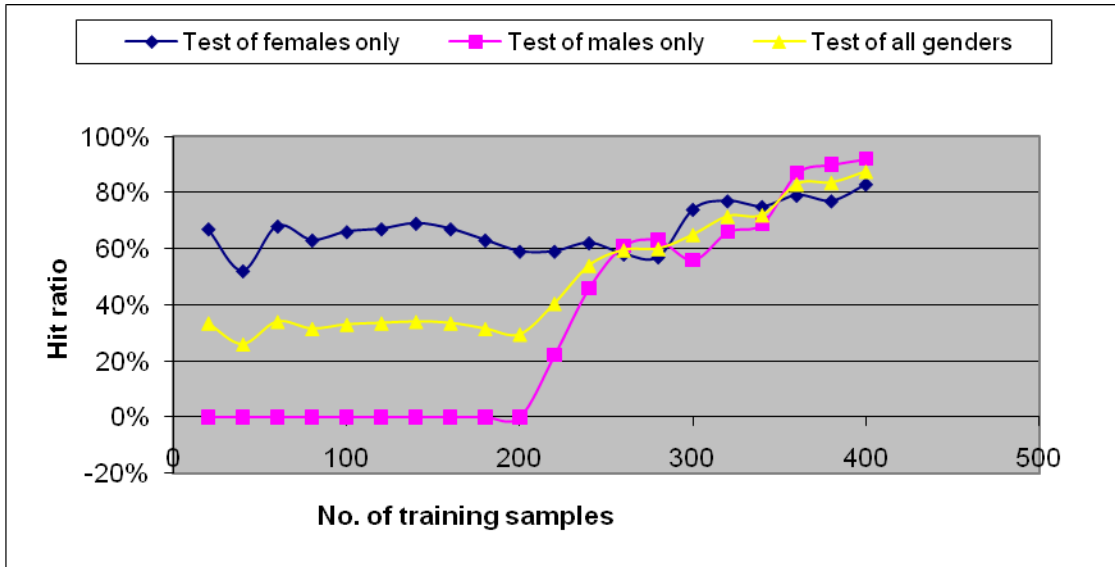
This approach implies combining Eigenfaces and SIFT approach together, by converting each face image (training set and testing set) into eigenface, and calculating SIFT key-points for that eigenface.

Figure (6) illustrates the steps of processing for achieving key-points of particular eigenface, figure (6-a) shows the pyramid of implementing Gaussian filter to the eigenface, figure (6-b) shows the pyramid of Different of Gaussian (DoG), figure (6-c) shows the locations of selected key-points before removing unnecessary points and the number of key-points are 57 points, figure (6-d) shows the locations of key-points (remain 48 points) after removing the location which have DoG value below than contrast threshold, figure (6-e) shows the locations of key-points (remain 45 points) after removing the locations which have DoG value above than curvature threshold, and the last figure (6-f) illustrates the final result of SIFT implementation, which shows the points with its scales and orientations.

Figure (7) illustrates the implementation of classifying face gender by using SIFT key-points of eigenfaces with different number of training images of eigenfaces for both genders (males and females).



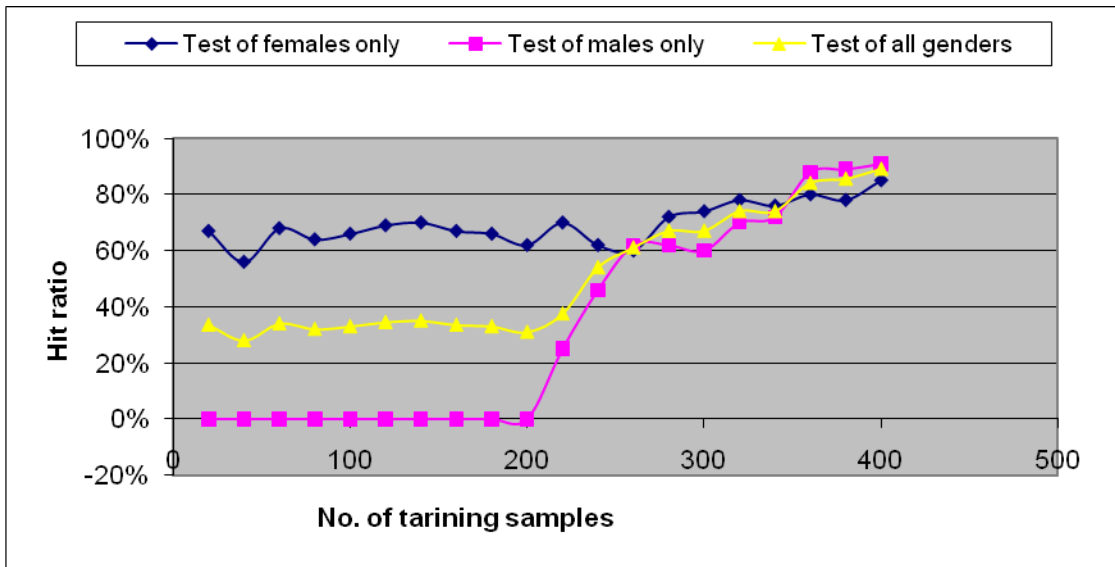
**Figure (6) Tasks of implementing the SIFT procedure on the eigenface, a) Pyramid of Gaussian filter of images, b) Pyramid of DoG, c) Locations of selected key-points before removing unnecessary points, d) Locations of selected key-points after applying contrast threshold, e) Locations of selected key-points after applying curvature threshold, f)Result of SIFT procedure, resulted key-points, scales, and orientations.**



**Figure (7) performance of classifying faces to their corresponding gender using SIFT key-points at different number of training eigenfaces images.**

**V-SIFT approach**

Figure (8) illustrates performance of classifying the faces into their corresponding gender using VSIFT approach.



**Figure (8) performance of classifying faces into their corresponding gender using Volume-SIFT approach at different numbers of trained eigenfaces**

### New approach

Figure (9) illustrates the performance of classifying the faces into their corresponding gender using the new approach (modifying VSIFT approach), new value was assigned to the scale dimension between octaves (0.75).

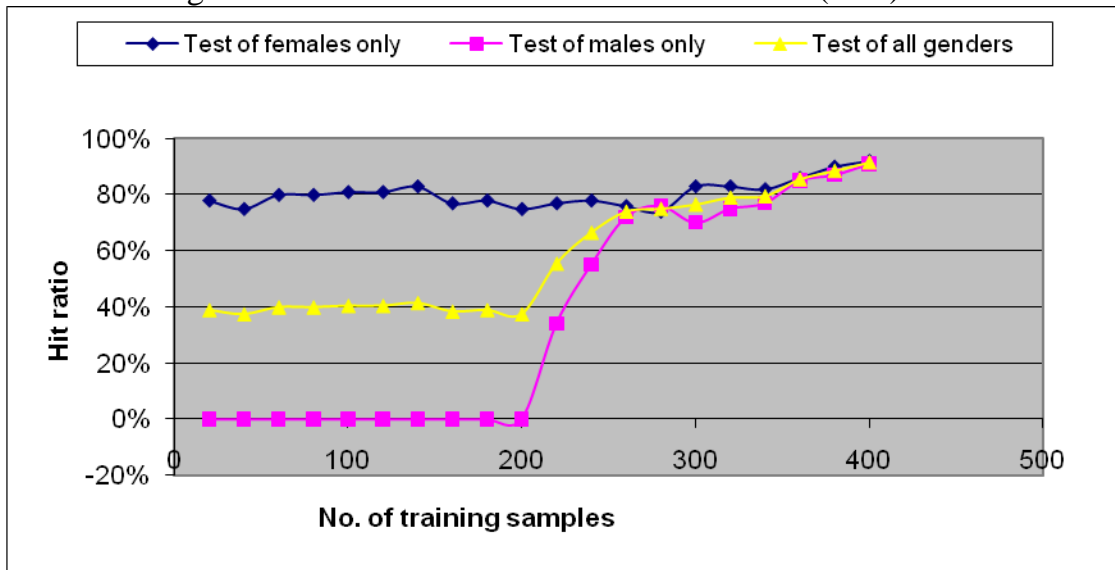


Figure (9) performance of classifying faces into their corresponding gender using new approach at different numbers of trained eigenfaces

### Results of all approaches

Figure (10) illustrates the performance comparison of all previous mentioned approaches to classify faces into their corresponding gender with different number of training samples.

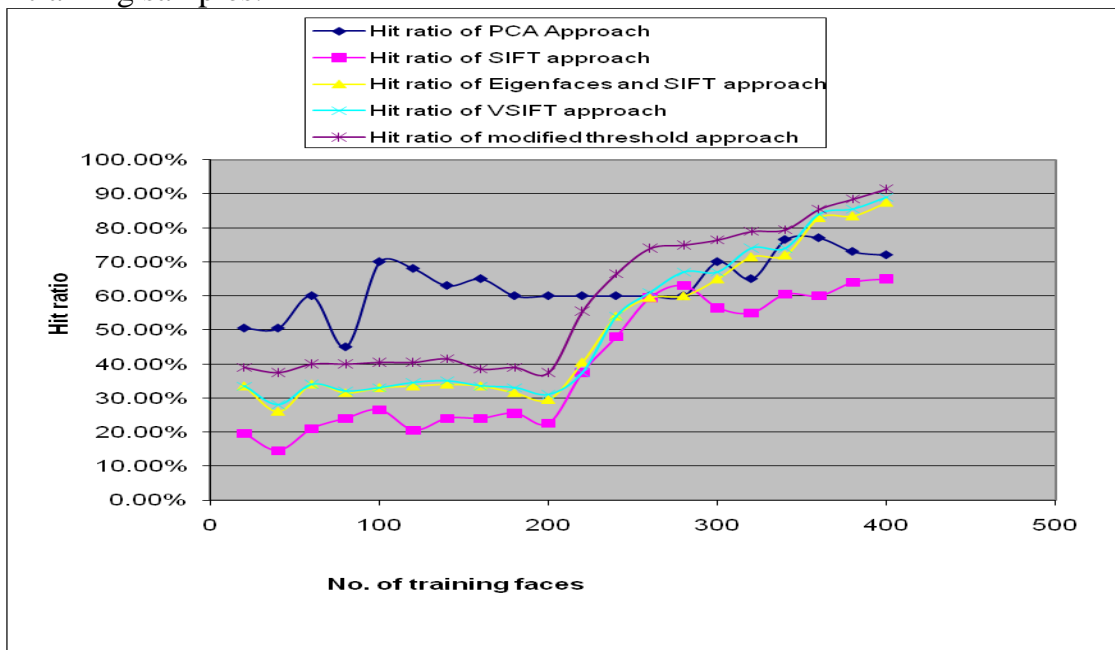


Figure (10) performance of all previous mentioned approaches to classify faces into their corresponding gender at different number of training samples.

## **Conclusions**

The classification performance of using PCA features are characterized by critical results, where the hit ratio of testing images which contain at faces of males only is 92% and females only is 9% when the numbers of training samples are 20, and this ratio decreased for males but increased for females. Thus, this approach has been proved it was not efficient experimentally.

When the number of training samples are above 220 images (half for males and half for females) the performance of using SIFT features began to be stable, and the hit ratio reached at 65% when the number of training samples arrive to 400 images. But this approach is not efficient, thus we used the Eigenfaces in the training and testing samples then extracting the SIFT features, that made the performance better than extracting SIFT features from original faces images, and the hit ration arrived to 87.5% when the numbers of training samples of eigenfaces are 400.

Using VDIFT approach gives us low performance, but the figure (10) shows that the performance of using new approach is very efficient, where; the hit ratio arrived to 91% and it is the best ration can be gotten for the classification of the faces into its corresponding gender. Thus this new approach will be more efficient as the numbers of training samples are increasing.



## References

- [1]. Koray Balci and Volkan Atalay (2002). PCA for Gender Estimation: Which Eigenvectors Contribute?. 16<sup>th</sup> International Conference on pattern Recognition, IEEE, Vol. 3, Pages 363-366.
- [2] Dr. P. K. Suri, Dr. Ekta Walia and Er. Amit Verma (2011). Face Detection and Gender Detection using Principal Component Analysis (PCA). IEEE, 3<sup>rd</sup> International Conference on Communication Software & Networks, pages 679-684.
- [3] Cong Geng and Xudong Jiang (2009). Face Recognition Using SIFT Features. 16<sup>th</sup> IEEE International Conference on Image Processing (ICIP), pages 3313-3316.
- [4] Morteza Zahedi and Sahar Yousefi (2011). Gender Recognition Based on SIFT Features. International Journal of Artificial Intelligence & Application (IJAIA), Vol. 2, No. 3.
- [5] Chin-Shu Chang and Kuo-Kuang Chen (2010). Human Face Recognition System Using Modified PCA Algorithm and ARM Platform. International Symposium on Computer, Communication, Control and Automation, Taiwan.
- [6]. Dr. H. B. Kekre, Sudeep D. Thepade and Tejas Chopra (2010). Face and Gender Recognition Using Principal Component Analysis. International Journal on Computer Science and Engineering (IJCSE). Vol. 02, No. 04, 959-969.
- [7]. Jian Zhang, Xianyun Fei and Young Zhang (2010). A New Method for Face Recognition Based on PCA Optimize Strategy. International Conference on Computer Application and System Modeling (ICCASM).
- [8]. David G. Lowe (2004). Distinctive Image Features from Scale Invariant Keypoints. International Journal of Computer Vision. IEEE, Vol. 6, Pages 91-110.
- [9]. Na Liu, Jianhuang Lai and Huining Qiu (2011). Robust Face Recognition by Sparse Local Features from a Single Image under Occlusion. 6<sup>th</sup> International Conference on Image and Graphics. IEEE , pages: 500-505.
- [10]. Suparna Parua, Apurba Das, Debasis Mazumdar, and Soma Mitra (2011). Determination of Feature Hierarchy from Gabor & SIFT Features for Face Recognition. 2<sup>nd</sup> International Conference on Emerging Applications of Information Technology. IEEE, pages: 257-260.

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