Identification of Untrained Facial Image in Combined Global and Local Preserving Feature Space

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Abstract

In real time applications, biometric authentication has been widely regarded as the most foolproof - or at least the hardest to forge or spoof. Several research works on face recognition based on appearance, features like intensity, color, textures or shape have been done over the last decade. In those works, mostly the classification is achieved by using the similarity measurement techniques that find the minimum distance among the training and testing feature set. When presenting this leads to the wrong classification when presenting the untrained image or unknown image, since the classification process locates at least one wining cluster that having minimum distance or maximum variance among the existing clusters. But for the real time security related applications, these new facial image should be reported and the necessary action has to be taken accordingly. In this paper we propose the following two techniques for this purpose:

i. Uses a threshold value calculated by finding the average of the minimum matching distances of the wrong classifications encountered during the training phase.
ii. Uses the fact that the wrong classification increases the ratio of within-class distance and between-class distance.

Experiments have been conducted using the ORL facial database and a fair comparison is made with these two techniques to show the efficiency of these techniques.

Keywords: Biometric Technology, Face Recognition, Adaptive clustering, Global Feature and Local Feature

1. INTRODUCTION

Biometrics is increasingly becoming important in our security-heightened world. As the level of security breaches and transaction fraud increases, the need for highly secure identification and personal verification technologies is becoming apparent. Biometric authentication has been widely regarded as the most foolproof - or at least the hardest to forge or spoof. Though various biometric authentication methods like fingerprint authentication, iris recognition, palm authentication exists, the increasing use of biometric technologies in high-security applications and beyond has stressed the requirement for highly dependable face recognition systems. Despite significant advances in face recognition technology, it has yet to be put to wide use in commerce or industry, primarily because the error rates are still too high for many of the applications in mind. These problems stem from the fact that existing systems are highly sensitive to environmental factors during image capture, such as variations in facial orientation, expression and lighting conditions. A comprehensive survey of still and video-based face recognition techniques can be found in [1]. Various methods have been proposed in the literature such as appearance based [2], elastic graph matching [3], neural network [4], line edge map [5] and support vector machines [6].

In appearance based approach we consider each pixel in an image as a coordinate in a high-dimensional space. In practice, this space, i.e. the full image space, is too large to allow robust and fast object recognition. A common way to resolve this problem is to reduce the feature dimensionality by preserving only the necessary features. Principal Component Analysis (PCA), Multidimensional Scaling (MDS), Linear Discriminant Analysis (LDA) [7] are some of the popular feature dimensionality reduction techniques that preserve only the global features and Locality Preserving Projections (LPP) [8, 9] is one of the feature dimension reduction technique that preserves only the local features. It builds a graph incorporating neighborhood information of the data set. Using the notion of the Laplacian of the graph, we then compute a transformation matrix, which maps the data points to a subspace. This linear transformation optimally preserves local neighborhood information in a certain sense. The representation map generated by the algorithm may be viewed as a linear discrete approximation to a continuous map that naturally arises from the geometry of the manifold.

The work [10] uses non-tensor product wavelet decomposition applied on the face image followed by PCA for dimensionality reduction and SVM for classification. The combination of 2D-LDA and SVM was used in [11] for recognizing various facial expressions like happy, neutral, angry, disgust, sad, fear and surprise. Also there are some approaches that dealt with 3D facial images. Reconstruction of 3D face from 2D face image based on photometric stereo that estimates the surface normal from shading information in multiple images is shown in [12]. In this paper, an exemplar pattern is synthesized using an illumination reference, known lighting conditions from at least three images, which requires a minimum of three known images for each category under arbitrary lighting conditions. In a paper [13], a metamorphosis system is formed with the combination of traditional free-form deformation (FFD) model and data interpolation techniques based on the proximity preserving Voronoi diagram. Though there exist many 3D facial image processing algorithms, still lot of works are going on in 2D itself, to achieve the most optimal results. In the work [14], a generative probability model is proposed, with which we can perform both extraction of features and combining them for recognition. Also in the work [15], they developed a probabilistic version of Fisher faces called probabilistic LDA. This method allows the development of nonlinear extensions that are not obvious in the standard approach, but it suffers with its implementation complexity.

In the work by us [16], we employ the combination of global feature extraction technique LDA and local feature extraction technique LPP, to achieve a high quality feature set called Combined Global and Local Preserving Features (CGLPF) that capture the discriminate features among the samples considering the different classes in the subjects. To reduce the effect of overlapping features, only the little amount of local features are eliminated by preserving all the global features in the first stage and the local features are extracted from the output of the first stage to produce good recognition result. This increases the robustness of face recognition against noises affecting global features and / or local features [17].

Measuring similarity or distance between two feature vectors is also a key step for any pattern matching applications. Similarity measurement techniques will be selected based on type of the data such as binary variable, categorical variable, ordinal variable, and quantitative variable. Most of the pattern matching applications are dealt with quantitative variables and many similarity measurement techniques exist for this category such as Euclidean distance, city block or Manhattan distance, Chebyshev distance, Minkowski distance, Canberra distance , Bray Curtis or Sorensen distance, angular separation, Bayesian[18], Masked Trace transform (MTT) [19] and correlation coefficient. Bayesian method replaces costly computation of nonlinear Bayesian similarity measures by inexpensive linear subspace projections and simple Euclidean norms, thus resulting in a significant computational speed-up for implementation with very large databases. Compared to the dimensionality reduction techniques, this method requires the probabilistic knowledge about the past information. MTT is a distance measure incorporating the weighted trace transforms in order to select only the significant features from the trace transform. The correlation based matching techniques [20, 21] determine the cross-correlation between the test image and all the reference images. When the target image matches the reference image exactly, the output correlation will be high. If the input contains multiple replicas of the reference image, resulting cross-correlation contains multiple peaks at locations corresponding to input positions.

Most of the similarity measurement techniques based on distance measurement requires a restriction that, the images in the testing set should be belong to at least any one of the subject in the training image set. Though the testing set images can contain large variations in the visual stimulus due to illumination conditions, viewing directions or poses, facial expressions, aging, and disguises such as facial hair, glasses, or cosmetics, these images should match with at least one of the subject used for training. It is because the classification is achieved there by finding the minimum distance or maximum variance among the training and testing feature set. Also the classification process locates at least one wining cluster that having minimum distance or maximum variance among the existing clusters. Hence in this work, we propose two techniques for identifying the unknown image presented during the testing phase. The first one uses a threshold value calculated by finding the average of the minimum matching distances of the wrong classifications encountered during the training phase. In the second method, we employ the fact that the wrong classification increases the ratio of within-class distance and between-class distance where as the correct classification decrease the ratio.

The rest of the paper is organized as follows: Section 2 describes the steps in creating the CGLPF space where our proposed adaptive techniques are applied. In section 3, our proposed techniques for identifying the untrained / unknown facial image are discussed. The facial images that are used and the results obtained using our adaptive techniques are presented in section 4. Also a comparison of our two adaptive facial image recognition results in the CGLPF space on 400 images from ORL image database is presented. The paper is concluded with some closing remarks in section 5.

2. COMBINED GLOBAL AND LOCAL PRESERVING FEATURES (CGLPF)

The combined approach that combines global feature preservation technique LDA and local feature preservation technique LPP to form the high quality feature set CGLPF is described in this section.

Preserving the Global Features

The mathematical operations involved in LDA, the global feature preservation technique is analyzed here. The fundamental operations are:

1. The data sets and the test sets are formulated from the patterns which are to be classified in the original space.
2. The mean of each data set μ_i and the mean of entire data set μ are computed.

$$\mu = \sum_i p_i \mu_i \tag{1}$$

where p_i is priori probabilities of the classes.

3. Within-class scatter S_w and the between-class scatter S_b are computed using:

$$S_w = \sum_j p_j * (cov_j) \quad (2)$$

$$S_b = \sum_j (x_j - \mu)(x_j - \mu) \quad (3)$$

where cov_j the expected covariance of each class is computed as:

$$cov_j = \prod_i (x_j - \mu_i) \quad (4)$$

Note that S_b can be thought of as the covariance of data set whose members are the mean vectors of each class. The optimizing criterion in LDA is calculated as the ratio of between-class scatter to the within-class scatter [7]. The solution obtained by maximizing this criterion defines the axes of the transformed space.

It should be noted that if the LDA is a class dependent type, for *L*-class *L* separate optimizing criterion are required for each class. The optimizing factors in case of class dependent type are computed using:

$$criterion_j = \mathrm{inv}\left(cov_j\right) \times S_b \quad (5)$$

For the class independent transform, the optimizing criterion is computed as:

$$criterion = \mathrm{inv}\left(S_W\right) \times S_b \quad (6)$$

4. The transformations for LDA are found as the Eigen vector matrix of the different criteria defined in the above equations.

5. The data sets are transformed using the single LDA transform or the class specific transforms.
   For the class dependent LDA,

$$transformed\_set\_\mathrm{j} = transform\_\ j^T \times set\_j \quad (7)$$

   For the class independent LDA,

$$transformed\_set = transform\_spec^T \times set^T \quad (8)$$

6. The transformed set contains the preserved global features which will be used as the input for the next stage local feature preservation. Since we eliminate only the very few components of local features while preserving global components this can be used as input for local feature preserving module.
   For the class dependent LDA,

$$x = transformed\_set\_j \quad (9)$$

   For the class independent LDA,

$$x = transformed\_set \quad (10)$$

In order to preserve the global features LDA is employed and an optimum of 90 percentages of global features is preserved and then the local feature extraction technique LPP is applied to preserve the local features. Based on various experiments, we have selected the optimum value as 90 percentages. Choosing a value less than 90 percentage results in the removal of more local features with the discarded unimportant global features whereas choosing a value more than 90 percentage results in the constraint that makes the features more difficult to discriminate from one another.

Adding Local Features

Actually the local features preserving technique seeks to preserve the intrinsic geometry of the data and local structure. The following are the steps to be carried out to obtain the Laplacian transformation matrix W_{LPP}, which we use to preserve the local features.

1. **Constructing the nearest-neighbor graph:** Let G denote a graph with k nodes. The i^{th} node corresponds to the face image x_i. We put an edge between nodes i and j if x_i and x_j are "close," i.e., x_j is among k nearest neighbors of x_i, or x_i is among k nearest neighbors of x_j. The constructed nearest neighbor graph is an approximation of the local manifold structure, which will be used by the distance preserving spectral method to add the local manifold structure information to the feature set.

2. **Choosing the weights:** The weight matrix S of graph G models the face manifold structure by preserving local structure. If node i and j are connected, put

$$S_{ij} = e^{\frac{-\left\| x_i - x_j \right\|^2}{t}} \tag{11}$$

where t is a suitable constant. Otherwise, put $S_{ij} = 0$.

3. **Eigen map:** The transformation matrix W_{LPP} that minimizes the objective function is given by the minimum Eigen value solution to the generalized Eigen value problem. The detailed study about LPP and Laplace Beltrami operator is found in [1, 21]. The Eigen vectors and Eigen values for the generalized eigenvector problem are computed using equation 16.

$$XLX^T W_{LPP} = \lambda XDX^T W_{LPP} \tag{12}$$

where D is a diagonal matrix whose entries are column or row sums of S, $D_{ii} = \Sigma_j S_{ji}$, $L = D - S$ is the Laplacian matrix. The i^{th} row of matrix X is x_j. Let $W_{LPP} = w_0, w_1, ..., w_{k-1}$ be the solutions of the above equation, ordered according to their Eigen values, $0 \le \lambda_0 \le \lambda_1 \le \ldots \le \lambda_{k-1}$. These Eigen values are equal to or greater than zero because the matrices XLX^T and XDX^T are both symmetric and positive semi-definite. Note that the two matrices XLX^T and XDX^T are both symmetric and positive semi-definite since the Laplacian matrix L and the diagonal matrix D are both symmetric and positive semi-definite.

4. By considering the transformation space W_{LDA} and W_{LPP}, the embedding is done as follows:

$$\begin{aligned} & x \rightarrow y = W^T x, \\ & W = W_{LDA} W_{LPP}, \\ & W_{LPP} = [w_0, w_1, ..., w_{k-1}] \end{aligned} \tag{13}$$

where y is a k-dimensional vector, W_{LDA}, W_{LPP} and W are the transformation matrices of LDA, LPP and CGLPF algorithms respectively. The linear mapping obtained using CGLPF best preserves the global discriminating features and the local manifold's estimated intrinsic geometry in a linear sense.

3. ADAPTIVE FACE RECOGNITION IN CGLPF SPACE

The two adaptive approaches that identifies and reports the new facial image for security related applications is described in this section. The first technique uses a threshold value calculated by finding the average of the minimum matching distances of the wrong classifications encountered during the training phase. Also the second one uses the fact that the wrong classification increases the ratio of within-class distance and between-class distance.

Technique based on Minimum Matching Distances of Wrong Classifications

The detailed operations involved in calculating the threshold that identifies the wrong classification and stresses the need of new cluster requirement is given here.

1. For the learning phase, let us consider X is a set of N sample images $\{x_1, x_2, \ldots, x_N\}$ taking values in an n-dimensional image space, and assume that each image belongs to one of c classes, $\{A_1, A_2, \ldots, A_c\}$. The training data set X_1 and the testing data set X_2 are formulated from the above patterns which are to be classified in the original space as:
$$X_1 = \{ x_{i,j} \;\|\; 1 \le i \le c \;\; \& \;\; 1 \le j \le m \}$$
$$X_2 = \{ x_{i,j} \;\|\; 1 \le i \le c \;\; \& \;\; m < j \le n \} \tag{14}$$
where m is the number of images used for training in the learning phase.

2. The combined global and local preserving feature space W for the just created training data set has been formed by employing the detailed procedure given in section 2.

3. Using the linear transformation mapping created in step 2, the training and testing image set with original n-dimensional image space has been mapped into an m-dimensional feature space, where $m << n$.
$$X_1 \to Y_1 = W^T X_1$$
$$X_2 \to Y_2 = W^T X_2 \tag{15}$$

4. By applying the similarity measurement technique like Euclidean distance, Manhattan distance, Bayesian or correlation coefficient methods, the images in the testing data set are mapped to a corresponding clusters in the training image set. The j^{th} testing image in X_2 is mapped to the cluster using,
$$X_2^j \to Y_2^j = \min\left(\sum_{i=1}^{m} dist\left(X_1^i, X_2^j\right) \right) \tag{16}$$

5. The wrong classifications encountered in the step 4, has been identified using,
$$\{ x_i^j \notin A_i \;\|\; 1 \le i \le c \;\; \& \;\; 1 < j \le n \} \tag{17}$$

6. The threshold value T is set from the minimum matching distances calculated in step 4 for the wrong classifications identified in step 5.

7. During the adaptive recognition phase, when any real time image pattern Z given in original space, the classification has been done and the minimum matching distance has been identified.

8. Based on the threshold value calculated in step 6, the requirement of the new cluster will be identified as:
$$Z \to Y_2^{j+1} = \min\left(\sum_{i=1}^{m} dist\left(X_1^i, Z\right) \right) > T \tag{18}$$

Technique based on Within-class and Between-class Distances

The operations involved in finding the ratio between within-class distance and between-class distance that identifies the wrong classification and stresses the need of new cluster requirement is presented here.

1. For the learning phase, let us consider X is a set of N sample training images $\{x_1,x_2,\ldots,x_N\}$ taking values in an n-dimensional image space that belongs to one of c classes, $\{A_1,A_2,\ldots,A_c\}$ and the testing data set Y are formulated in the original space.

2. By applying the detailed procedure given in section 2, the combined global and local preserving feature space W for the just created training data set X has been formed.

3. The training and testing image set with original n-dimensional image space has been mapped into an m-dimensional feature space, where $m << n$ using the linear transformation mapping created in step 2,

$$X \rightarrow X^r = W^T X$$

$$Y \rightarrow Y^r = W^T Y \tag{19}$$

4. By applying the similarity measurement technique like Euclidean distance, Manhattan distance, Bayesian or correlation coefficient methods, the images in the testing data set are mapped to a corresponding clusters in the training image set. The j^{th} testing image in Y is mapped to the cluster using,

$$Y_j \rightarrow A_k = \min\left(\sum_{i=1}^{n} dist\left(X_r^i, Y_r^j\right)\right) \tag{20}$$

5. The within-class distance is calculated using,

$$WCD = \sum_1^c \sum \left(x - \mu_i\right) \tag{21}$$

where $x \varepsilon A_i$ and μ_i is the mean of the cluster A_i.

6. The between-class distance is formed by using,

$$BCD = \sum_1^c \left(\mu - \mu_i\right) \tag{22}$$

where μ_i is the mean of the cluster A_i and μ is the mean of all the clusters.

7. The ratio R is formed using the within-class distance and the between-class distance calculated in step 5 and step 6.

8. During the adaptive recognition phase, when any real time image pattern Z given in original space, the classification has been done and the ratio (Rnew) has been identified.

9. Based on the threshold value R and the ratio R_{new} calculated in step 7 and 8, the requirement of the new cluster will be identified as:

$$Z \rightarrow A_{c+1} = R_{new} > R \tag{23}$$

Theoretically, the above equation is true, but based on various experiments, if the new ratio is greater than an optimum value of 110 percentages of the previous ratio, we can adapt a new cluster with Z as the mean of the new cluster. Choosing a value less than 110 percentages results in the division of one category of information into two groups unnecessarily whereas choosing a value more than 110 percentages results in wrongly categorizing different category of information into single group.

In the above technique based on minimum matching distances of wrong classifications, the threshold value is calculated only once during the learning phase and which will not be changed in the recognition phase where as the ratio calculated in the second technique, will be updated regularly with each real time image presented during the adaptive recognition phase.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section, the images that are used in this work and the results of adaptive facial image recognition obtained with the newly proposed techniques in the CGLPF feature set are presented. For classification experiments, the facial images from the ORL facial image databases are used. The ORL database contains a total of 400 images containing 40 subjects each with 10 images in different poses. Figure 1 show the sample images used in our experiments collected from ORL database. The images of ORL database are already aligned and no additional alignments are done by us. For normalization purpose, we make all the images into equal size of 50 x 50 pixels by doing the bilinear image resizing.

The database is separated into two sets as follows: i) the training and testing image sets for the learning phase are formed by taking any 20 subjects with varying number of images per subject ii) the real time testing image set for the adaptive recognition phase is formed by a combination of all the remaining images from the 20 subjects used in learning phase and all the images from the remaining 20 subjects in the ORL database, thus always the recognition phase uses a minimum of 200 images. It is in usual practice that the testing image set will be a part of training image set. But one cannot always expect that all testing images will from a part of training image set. Hence, in our analysis, we exclude the testing image in the recognition phase from that of image set in learning phase for all subjects.

FIGURE 1: The sample set of images collected from ORL database

During the learning phase, the training and testing image set are formed by varying the number of images per subject and combined global and local preserving feature space is formed using the training image set. The training and testing images in the learning phase are then projected into the CGLPF space and the threshold value is calculated after applying the Euclidean based similarity measurement technique as given in section 3. In the experimental or recognition phase, the testing images are given one by one and the result of applying our first technique may be any one of the following: i) the identified cluster may be the correct corresponding cluster of the testing image, ii) the testing image may not belong to any of the training clusters, which should be identified as the untrained image, iii) the wrong classification of testing image belonging to one cluster into any of the other trained clusters, iv) wrongly classifying untrained testing image into any of the trained clusters. Among the four outputs, the first two cases are the correct recognition and the last two are treated as errors. The error rate is calculated by repeating this procedure for all the images in the testing set of the recognition phase. This error rate calculation process is repeated by varying the number of images used in the learning and recognition phase in the CGLPF space and the results are tabulated in table 1.

Learning Phase				**Recognition Phase**	**Error Rate in %**
Training images / Subject (i)	**Testing images / Subject (j)**	**Total Training images (20 * i)**	**Total Testing images (20 *j)**	**Total Testing Images**	
1	1	20	20	360	10.28
2	1	40	20	340	9.71
2	2	40	40	320	9.38
3	1	60	20	320	7.5
3	2	60	40	300	7.33
3	3	60	60	280	6.79
4	1	80	20	300	5
4	2	80	40	280	4.64
4	3	80	60	260	4.23
4	4	80	80	240	3.75
5	1	100	20	280	2.14
5	2	100	40	260	1.92
5	3	100	60	240	1.67
5	4	100	80	220	1.36

TABLE 1: Error rate obtained by applying the technique based on minimum matching distances of wrong classifications in the CGLPF space

The first column in the table shows the number of training images per subject taken in the learning phase and the second column indicates the number of testing images per subject considered. The total number of training and testing images used in the learning phase is shown in third and fourth column respectively. Since 20 subjects have been considered in the learning phase, the third and fourth column values are obtained by the 20 multiples of first and second columns respectively. The next column shows the total number of testing images considered in the recognition phase i.e., the images in the ORL database excluding the images used in the learning phase. The last column shows the error rate obtained by using our proposed technique.

In the second part of our experiment, the second adaptive technique based on within-class and between-class distance ratio is applied. As in the first part of our experiments, during the learning phase, the training and testing image set are formed by varying the number of images per subject. From the images in the training image set, the combined global and local preserving feature space is formed as given in section 2. The training and testing images in the learning phase are then projected into the CGLPF space and the Euclidean based similarity measurement technique is used to categorize the images in the testing set. From this the, ratio between the within-class and between-class distances are calculated as given in section 3. In the experimental or recognition phase, the testing images are given one by one and our second technique is applied, the results may be any one of the following cases: i) the identified cluster may be the correct corresponding cluster of the testing image, ii) the testing image may not belong to any of the training clusters, which should be identified as the untrained image, iii) the wrong classification of testing image belonging to one cluster into any of the other trained clusters, iv) wrongly classifying untrained testing image into any of the trained clusters. In these four outputs, the first two cases are the correct recognition and the last two are treated as errors. After performing the recognition steps, once again the within-cluster distance, between-cluster distance are calculated and the ratio is updated accordingly to adapt to the next recognition. This process is repeated for all the images in the testing set and the same type of experiments have been conducted with various numbers of training and testing images in the learning phase and the results are tabulated in table 2.

Learning Phase				Recognition Phase	Error Rate in %
Training images / Subject (i)	Testing images / Subject (j)	Total Training images (20 * i)	Total Testing images (20 *j)	Total Testing Images	
1	1	20	20	360	6.67
2	1	40	20	340	6.47
2	2	40	40	320	5.94
3	1	60	20	320	4.69
3	2	60	40	300	4.33
3	3	60	60	280	3.93
4	1	80	20	300	3.33
4	2	80	40	280	2.86
4	3	80	60	260	2.31
4	4	80	80	240	2.08
5	1	100	20	280	1.43
5	2	100	40	260	1.15
5	3	100	60	240	0.83
5	4	100	80	220	0.45

TABLE 2: Error rate obtained by applying the technique based on within-class, between-class distances in the CGLPF space

From the above two tables, it can be noted that, the technique based on within-class and between-class distance performs well than the technique based on minimum matching distance of the wrong classifications. It is because the threshold value used in the former one is fixed whereas the ratio used in the later is varying according to the real time testing image presented during the adaptive recognition phase.

It is the nature that the time complexity is increasing when using the combined schemes compared to using the techniques individually. But in our proposed method, the training is done offline and the testing is done in the real time or online. In the online phase, it is only going to project the testing image into the CGLPF feature set which is having only lower dimensions compared to the cases when the techniques are used individually. Hence when we employ our method in real time applications, there is no delay in the online and the offline delay does not cause any considerations in the real time processing.

5. CONCLUSIONS

Two techniques based on minimum matching distance of wrong classifications and ratio between within-class and between-class distance in combined global and local information preserving feature space for identifying the untrained images have been implemented and tested using standard facial image database ORL. The feature set created is an extension to the Laplacian faces used in Xiaofei He et al, where they use the PCA only for reducing the dimension of the input image space, and we use LDA for preserving the discriminating features in the global structure. The CGLPF feature set created using the combined approach retains the global information and local information, which makes the recognition insensitivity to absolute image intensity and insensitivity to contrast and local facial expressions.

In several face recognition applications, the classification process locates at least one training image when presenting the untrained or unknown image in the recognition phase. But for the security related applications, these new facial image should be reported and the necessary action has to be taken accordingly. In this work it is observed that the two proposed techniques in CGLPF space which can be enabled for these purpose, show the reduced error rate and it is superior to the conventional feature spaces when the images are subjected to various expressions and pose changes. Also the technique based on within-class and between-class distance performs well than the technique based on minimum matching distance of the wrong classifications. It is because the threshold value used in the former one is fixed whereas the ratio used in the later is varying according to the real time testing image presented during the adaptive recognition phase. Therefore, the technique based on the ratio between within-class and between-class distance in CGLPF feature space seems to be an attractive choice for many real time facial related image security applications.

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