Face Recognition

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Abstract

Face recognition has been one of the most interesting and important research fields in the past two decades. The reasons come from the need of automatic recognitions and surveillance systems, the interest in human visual system on face recognition, and the design of human-computer interface, etc. These researches involve knowledge and researchers from disciplines such as neuroscience, psychology, computer vision, pattern recognition, image processing, and machine learning, etc. A bunch of papers have been published to overcome difference factors (such as illumination, expression, scale, pose, ……) and achieve better recognition rate, while there is still no robust technique against uncontrolled practical cases which may involve kinds of factors simultaneously. In this report, we'll go through general ideas and structures of recognition, important issues and factors of human faces, critical techniques and algorithms, and finally give a comparison and conclusion. Readers who are interested in face recognition could also refer to published surveys [1-3] and website about face recognition [4]. To be announced, this report only focuses on color-image-based (2D) face recognition, rather than video-based (3D) and thermal-image-based methods.

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1. Introduction to Face Recognition: Structure and Procedure

In this report, we focus on image-based face recognition. Given a picture taken from a digital camera, we'd like to know if there is any person inside, where his/her face locates at, and who he/she is. Towards this goal, we generally separate the face recognition procedure into three steps: **Face Detection**, **Feature Extraction**, and **Face Recognition** (shown at Fig. 1).

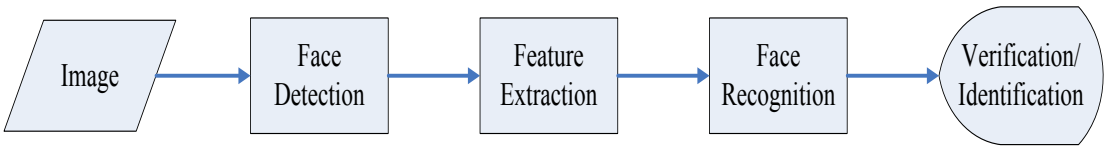


Figure 1: Configuration of a general face recognition structure

Face Detection:

The main function of this step is to determine (1) whether human faces appear in a given image, and (2) where these faces are located at. The expected outputs of this step are patches containing each face in the input image. In order to make further face recognition system more robust and easy to design, **face alignment** are performed to justify the scales and orientations of these patches. Besides serving as the pre-processing for face recognition, face detection could be used for region-of-interest detection, retargeting, video and image classification, etc.

Feature Extraction:

After the face detection step, human-face patches are extracted from images. Directly using these patches for face recognition have some disadvantages, first, each patch usually contains over 1000 pixels, which are too large to build a robust recognition system[1]. Second, face patches may be taken from different camera alignments, with different face expressions, illuminations, and may suffer from occlusion and clutter. To overcome these drawbacks, feature extractions are performed to do information packing, dimension reduction, salience extraction, and noise cleaning. After this step, a face patch is usually transformed into a **vector with fixed dimension** or a set of **fiducial points and their corresponding locations**. We will talk more detailed about this step in Section 2. In some literatures, feature extraction is either included in face detection or face recognition.

Face Recognition:

After formulizing the representation of each face, the last step is to recognize the

[1] We'll introduce the concept of "curse of dimensionality" in Section 2.6.

identities of these faces. In order to achieve automatic recognition, a face database is required to build. For each person, several images are taken and their features are extracted and stored in the database. Then when an input face image comes in, we perform face detection and feature extraction, and compare its feature to each face class stored in the database. There have been many researches and algorithms proposed to deal with this classification problem, and we'll discuss them in later sections. There are two general applications of face recognition, one is called **identification** and another one is called **verification**. Face identification means given a face image, we want the system to tell who he / she is or the most probable identification; while in face verification, given a face image and a guess of the identification, we want the system to tell true or false about the guess. In fig. 2, we show an example of how these three steps work on an input image.

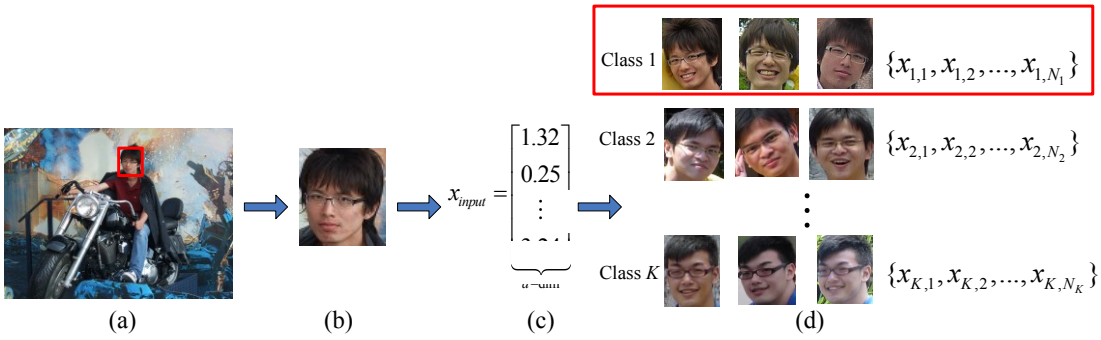


Figure 2: An example of how the three steps work on an input image. (a) The input image and the result of face detection (the red rectangle) (b) The extracted face patch (c) The feature vector after feature extraction (d) Comparing the input vector with the stored vectors in the database by classification techniques and determine the most probable class (the red rectangle). Here we express each face patch as a *d*-dimensional vector, the vector $x_{m,n}$ as the n_{th} vector in the m_{th} class, and N_k as the number of faces stored in the k_{th} class.

2. Fundamental of pattern recognition

Before going into details of techniques and algorithms of face recognition, we'd like to make a digression here to talk about pattern recognition. The discipline, pattern recognition, includes all cases of recognition tasks such as speech recognition, object recognition, data analysis, and face recognition, etc. In this section, we won't discuss those specific applications, but introduce the basic structure, general ideas and general concepts behind them.

The general structure of pattern recognition is shown in fig.3. In order to generate a system for recognition, we always need data sets for building categories and compare similarities between the test data and each category. A test data is usually called

a “query” in image retrieval literatures, and we will use this term throughout this report. From fig. 3, we can easily notice the symmetric structure. Starting from the data sets side, we first perform dimension reduction[2] on the stored raw data. The methods of dimension reduction can be categorized into data-driven methods and domain-knowledge methods, which will be discussed later. After dimension reduction, each raw data in the data sets is transformed into a set of features, and the classifier is mainly trained on these feature representations. When a query comes in, we perform the same dimension reduction procedure on it and enter its features into the trained classifier. The output of the classifier will be the optimal class (sometimes with the classification accuracy) label or a rejection note (return to manual classification).

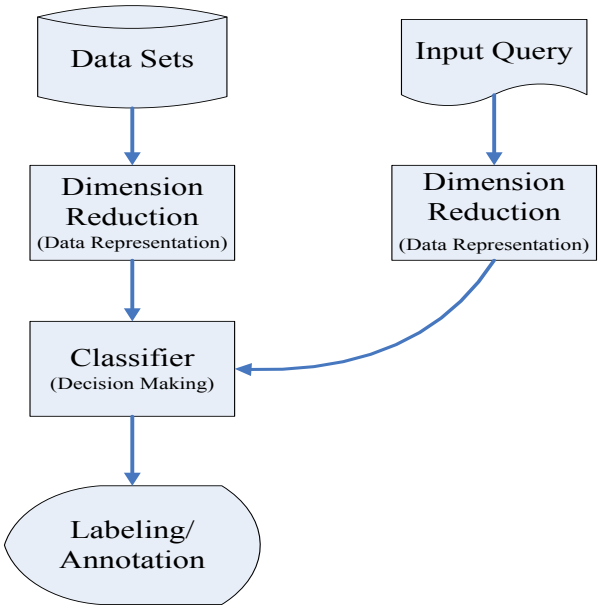


Figure 3: The general structure of a pattern recognition system

2.1Notation

There are several conventional notations in the literatures of pattern recognition and machine learning. We usually denote a matrix with an upper-case character and a vector with a lower-case one. Each sample in the training data set with *N* samples is expressed as $\{x_n^T, y_n^T\}$ for the supervised learning case (the label is known for each sample) and $\{x_n^T\}$ for the unsupervised case. The input query is represented as x without the indicator *T* to distinguish from the training set. When doing linear projection for dimension reduction, we often denote the projection vector as w and the projection matrix as W.

[2] We have seen in section 1, the term, dimension reduction, is also called feature extraction, salience extraction, etc. We use this term here in order to achieve coherence with Jain et al. [5], and we’ll discuss more about dimension reduction in 2.3.

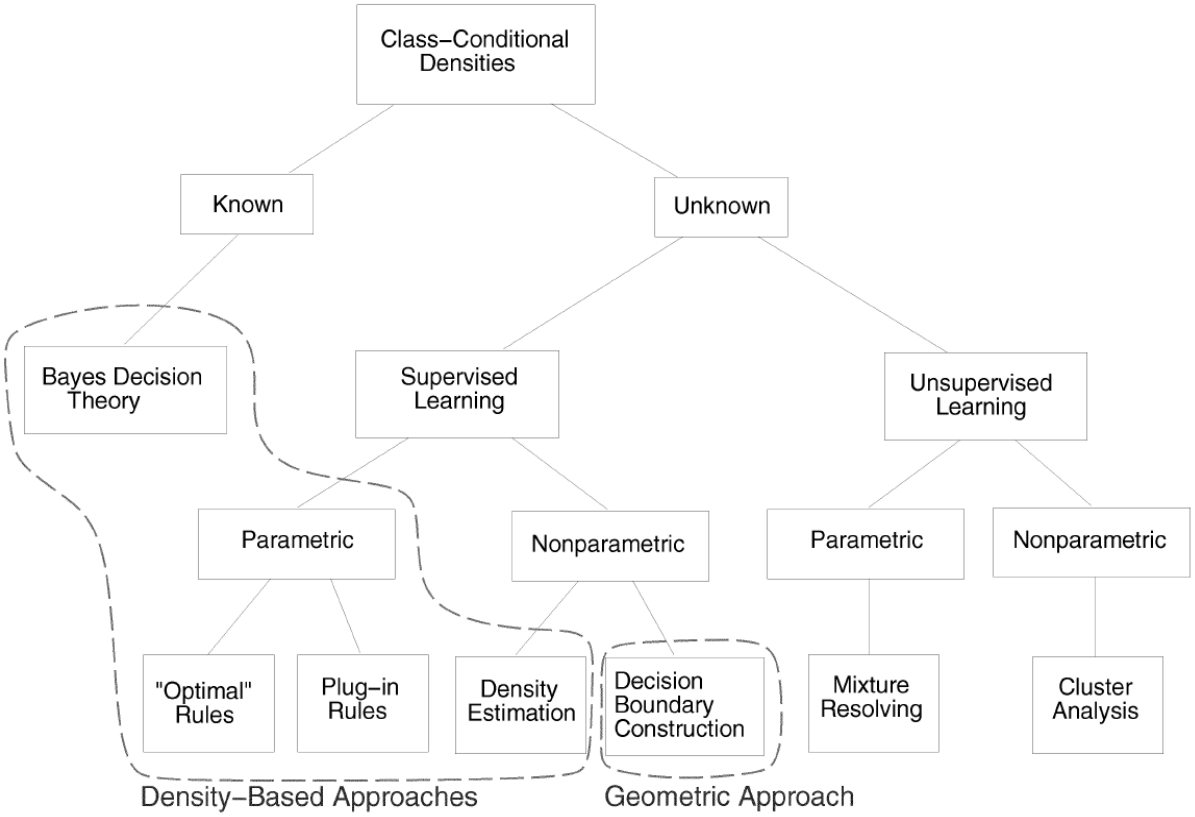


Figure 4: Various approaches in statistical pattern recognition. More details are discussed in [5].

2.2Different kinds of pattern recognition (four categories)

Following the definition of Jain et al. [5], Techniques of pattern recognition can be classified into four categories: Template matching, statistical approaches, syntactic approach, and neural networks. The template matching category builds several templates for each label class and compares these templates with the test pattern to achieve a suitable decision. The statistical approaches is the main category that will be discussed in this report, which extracts knowledge from training data and uses different kinds of machine learning tools for dimension reduction and recognition. Fig. 4 shows the categories of the statistical approach.

The syntactic approach is often called the rule-based pattern recognition, which is built on human knowledge or some physical rules, for example, the word classification and word correction requires the help of grammars. The term, knowledge, is referred to the rule that the recognition system uses to perform certain actions. Finally, the well-know neural networks is a framework based on the recognition unit called perceptron. With different numbers of perceptrons, layers, and optimization criteria, the neural networks could have several variations and be applied to wide recognition cases.

2.3 Dimension Reduction: Domain-knowledge Approach and Data-driven Approach

Dimension reduction is one of the most important steps in pattern recognition and machine learning. It's difficult to directly use the raw data (ex. face patches) for pattern recognition not only because significant parts of the data haven't been extracted but also because the extremely high dimensionality of the raw data. Significant parts (for recognition purposes or the parts with more interest) usually occupy just a small portion of the raw data and cannot directly be extracted by simple methods such as cropping and sampling. For example, a one-channel audio signal usually contains over 10000 samples per second, and there will be over 1800000 samples for a three minute-long song. Directly using the raw signal for music genre recognition is prohibitive and we may seek to extract useful music features such as pitch, tempo, and information of instruments which could better express our auditory perception. The goal of dimension reduction is to extract useful information and reduce the dimensionality of input data into classifiers in order to decrease the cost of computation and solve the curse of dimensionality problem.

There're two main categories of dimension reduction techniques: domain-knowledge approaches and data-driven approaches. The domain-knowledge approaches perform dimension reduction based on knowledge of the specific pattern recognition case. For example, in image processing and audio signal processing, the discrete Fourier transform (DFT) discrete cosine transform (DCT) and discrete wavelet transform are frequently used because of the nature that human visual and auditory perception have higher response at low frequencies than high frequencies. Another significant example is the use of language model in text retrieval which includes the contextual environment of languages.

In contrast to the domain-knowledge approaches, the data-driven approaches directly extract useful features from the training data by some kinds of machine learning techniques. For example, the eigenface which will be discussed in Section 5.11 determines the most important projection bases based on the principal component analysis which are dependent on the training data set, not the fixed basis like the DFT or DCT. In section 5, we'll see more examples about these two dimension reduction categories.

2.4 Two tasks: Unsupervised Learning and Supervised Learning

There're two general tasks in pattern recognition and machine learning: supervised learning and unsupervised learning. The main difference between these two tasks is if the label of each training sample is known or unknown. When the label is known, then during the learning phase in pattern recognition, we're trying to model the rela-

tion between the feature vectors and their corresponding labels, and this kind of learning is called the supervised learning. On the other hand, if the label of each training sample is unknown, then what we try to learn is the distribution of the possible categories of feature vectors in the training data set, and this kind of learning is called the unsupervised learning. In fact, there is another task of learning called the semi-supervised learning, which means only part of the training data has labels, while this kind of learning is beyond the scope of this report.

2.5Evaluation Methods

Besides the choices of pattern recognition methods, we also need to evaluate the performance of the experiments. There are two main evaluation plots: the ROC (receiver operating characteristics) curve and the PR (precision and recall) curve. The ROC curve examines the relation between the true positive rate and the false positive rate, while the PR curve extracts the relation between detection rate (recall) and the detection precision. In the two-class recognition case (for example, face and non-face), the true positive means the portion of face images to be detected by the system, while the false positive means the portion of non-face images to de detected as faces. The term true positive here has the same meaning as the detection rate and recall and we give a detailed description in table 1 and table 2. In fig. 5, we show examples of the PR curve. In addition to using curves for evaluation, there're some frequently used values for performance judgments, and we summarize them in table 3.

The threshold used to decide the positive or negative for a given case plays an important role in pattern recognition. With low threshold, we could achieve high true positive rate but also high false positive rate, and vice versa. To be noticed, each point on the ROC curve or PR curve corresponds to a specific threshold used.

The terms positive and negative reveal the asymmetric condition on detection tasks where one class is the desired pattern class and another class is the complement class. While in tasks that each class has equal importance or similar meaning (for example, each class denotes one kind of object), the error rate is much preferred.

Table 1: The definition of true positive and false positive

Ground truth \ detection	Detected (positive)	Rejected (negative)
Desired class	True positive (TP)	False negative (FN)
Complement class	False positive (FP)	True negative (TN)

(The ground truth means the given labels of the validation samples)

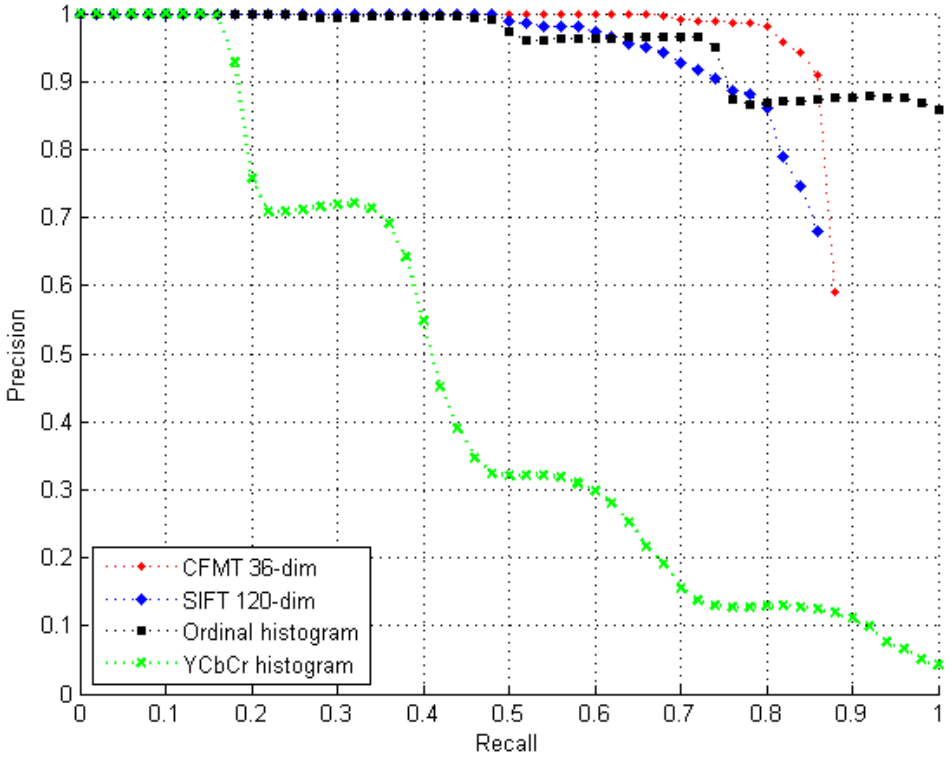


Fig 5: An example of the PR curve. This is the experimental result of the video fingerprinting technique, where five different methods are compared. The horizontal axis indicates the recall and the vertical axis indicates the precision. When comparing the performance among difference techniques, we estimate the area under each curve, and the larger the area, the better the performance.

Table 2: The definition of recall and precision

Term	Definition
Recall (R)	# of true positive / # of all desired patterns in the validation set
Precision (P)	# of true positive / # of all detected patterns

Table 3: Widely-used evaluation values

Evaluation value	Definition and usage
F1 score	$2 \times \mathrm{P} \times \mathrm{R}/(\mathrm{P}+\mathrm{R})$ This score is used to give a summary of the PR curve.
True positive & False positive	Many papers use these terms to show and compare the experimental results, while as we know, modifying the threshold could change both these two values. The ROC curve and the PR curve can show the whole performance of a specific algorithm over all possible threshold values
Error rate	# of misclassifications / # of samples in the validation set

Table 4: The definition of the four vectors in the statistical pattern recognition

Factor	Definition
N	The size of training data set. In the statistical pattern recognition, the knowledge of dimension reduction and classification is extracted from the training set, so the choices and the number of samples in the training set play important roles in building a robust recognition system. There have been many researches focusing on how to deal with limited training data size and how to increase the data size by some artificial methods.
d	The dimensionality of the feature vectors. In general, more dimensions included will result in better performance.
C	The number of classes. This term determines the scope of the recognition task. For example, face detection task could be seen as a two-class recognition task, while face recognition is a multi-class task.
h	The complexity of the classifier. There is no apparent formula to evaluate the complexity and the most popular judgment is the number of parameters of the adopted classifier.

Table 5: The task to be considered in the statistical pattern recognition and their relationship

Over-fitting/ under-fitting	When training a classifier, we can expect that adopting higher complexity ***h*** will achieve lower error rate on the training set. While for unseen data (data that will appear for classification later), this classifier may has poor performance because we don't have sufficient large training data size ***N*** to include all cases of data. On the other hand, if we adopt lower-complexity classifiers, the performance for training data and unseen data will both be poor. To train a higher-complexity classifier, we need a larger training data size to capture the reliable statistical properties. For a certain training data size, there is a suitable complexity ***h*** to be chosen, which can be estimate by the cross validation method. In the statistical pattern recognition category, what we are seeking is the generalization performance (the performance for unseen data), rather than the performance on the training data. If we adopt a higher complexity than a suitable one, we'll get a lower training error but higher generalized error, this condition is called "over-fitting". In contrast, if a lower complexity is sued, we'll achieve both higher error rates on these two cases, and this condition is called "under-fitting".
The curse of dimensionality	With higher dimensionality ***d***, we need large training data size ***N*** to capture the approximate distribution of the desired classes. While in many cases, data acquisition is fairly difficult and only a small data size is available, then we may suffer from the curse of dimensionality problem which results in poor statistical estimation and inference. To solve this problem, we need to perform dimension reduction.

2.6Conclusion

The tasks and cases discussed in the previous sections give an overview about pattern recognition. To gain more insight on the performance of pattern recognition techniques, we need to take care about some important factors. In template matching, the number of templates for each class and the adopted distance metric directly affects the recognition result. In statistical pattern recognition, there are four important factors: **the size of the training data *N*, the dimensionality of each feature vector *d*, the number of classes *C*, and the complexity of the classifier *h***, and we summarize their meanings and relations in table 4 and table 5. In syntactic approach, we expect that the more rules are considered, the higher recognition performance we can achieve, while the system will become more complicated. And sometimes, it's hard to transfer and organize human knowledge into algorithms. Finally in neural networks, the number of layers, the number of used perceptrons (neurons), the dimensionality of feature vectors, and the number of classes all have effects on the recognition performance. More interesting, the neural networks have been discussed and proved to have closed relationships with the statistical pattern recognition techniques [5].

3. Issues and factors of human faces

In section 2, we have introduced the general picture of pattern recognition, and from this section on, we'll go into one of its applications, face recognition. When focusing on a specific application, besides building the general structure of pattern recognition system, we also need to consider the intrinsic properties of the domain-specific data. For example, to analyze music or speech, we may first transform the input signal into frequency domain or MFCC (Mel-frequency cepstral coefficients) because features represented in these domain have been proved to better capture human auditory perception. In this section, we'll talk about the domain-knowledge of human faces, factors that result in face-appearance variations in images, and finally list important issues to be considered when designing a face recognition system.

3.1Domain-knowledge of human faces and human visual system

3.1.1 Aspects from psychophysics and neuroscience

There are several researches in psychophysics and neuroscience studying about how we human performs recognition processes, and many of them have direct relevance to engineers interested in designing algorithms or systems for machine recognition of faces. In this subsection, we briefly review several interesting aspects. The first

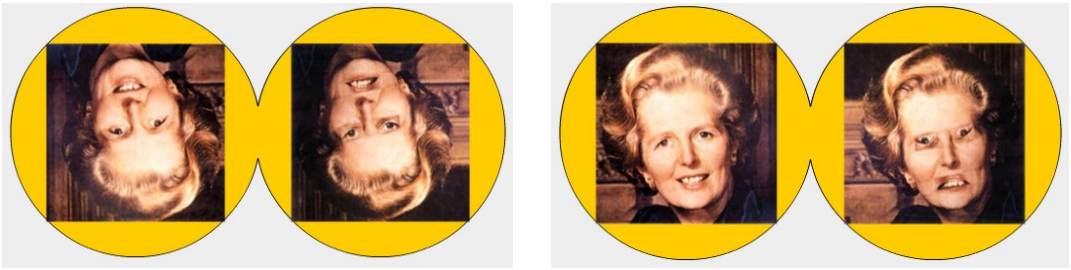
argument in these disciplines is that whether face recognition a dedicated process against other object recognition tasks. Evidences that (1) faces are more easily remembered by humans than other objects when presented in an upright orientation and (2) prosopagnosia patients can recognize faces from other objects but have difficulty in identifying the face support the viewpoint of face recognition as a dedicated process. While recently, some findings in human neuropsychology and neuroimaging suggest that face recognition may not be unique [2].

3.1.2 Holistic-based or feature-based

This is another interesting argument in psychophysics / neuroscience as well as in algorithm design. The holistic-based viewpoint claims that human recognize faces by the global appearances, while the feature-based viewpoint believes that important features such as eyes, noses, and mouths play dominant roles in identifying and remembering a person. The design of face recognition algorithms also apply these perspectives and will be discussed in Section 5.

3.1.3 Thatcher Illusion

The Thatcher illusion is an excellent example showing how the face alignment affects human recognition of faces. In the illusion shown in the fig. 6, eyes and mouth of an expressing face are excised and inverted, and the result looks grotesque in an upright face. However, when shown inverted, the face looks fairly normal in appearance, and the inversion of the internal features is not readily noticed.



(a) (b)

Figure 6: The Thatcher Illusion. (a) The head is located up-side down, and it's hard to notice that the eyes are pasted in the reverse direction in the right-side picture, while in (b) we can easily recognize the strange appearance. [6]

3.2Factors of human appearance variations

There are several factors that result in difficulties of face detection and face recognition. Except the possible low quality driven from the image acquisition system, we focus on the angle of human faces taken by the camera and the environment of photo acquisition. There are generally six factors we need to concern: (1) illumination,

(2) face pose, (3) face expression, (4) RST (rotation, scale, and translation) variation, (5) clutter background, and (6) occlusion. Table 6 lists the details of each factor.

Table 6: The list and description of the six general factors

Illumination	The illumination variation has been widely discussed in many face detection and recognition researches. This variation is caused by various lighting environments and is mentioned to have larger appearance difference than the difference caused by different identities. Fig. 7 shows the example of illumination changes on images of the same person, and it's obviously that under some illumination conditions, we can neither assure the identification nor accurately point out the positions of facial features.
Pose	The pose variation results from different angles and locations during the image acquisition process. This variation changes the spatial relations among facial features and causes serious distortion on the traditional appearance-based face recognition algorithms such as eigenfaces and fisherfaces. An example of pose variation is shown in fig. 8.
Expression	Human uses different facial expressions to express their feelings or tempers. The expression variation results in not only the spatial relation change, but also the facial-feature shape change.
RST variation	The RST (rotation, scaling, and translation) variation is also caused by the variation in image acquisition process. It results in difficulties both in face detection and recognition, and may require exhaustive searching in the detection process over all possible RST parameters.
Cluttering	In addition to the above four variations which result in changes in facial appearances, we also need to consider the influence of environments and backgrounds around people in images. The cluttering background affects the accuracy of face detection, and face patches including this background also diminish the performance of face recognition algorithms.
Occlusion	The occlusion is possibly the most difficult problem in face recognition and face detection. It means that some parts of human faces are unobserved, especially the facial features.

For our future works, we'll pay more attention on illumination-invariant, multi-view detection and recognition, and partial observation situations which haven't been well solved.

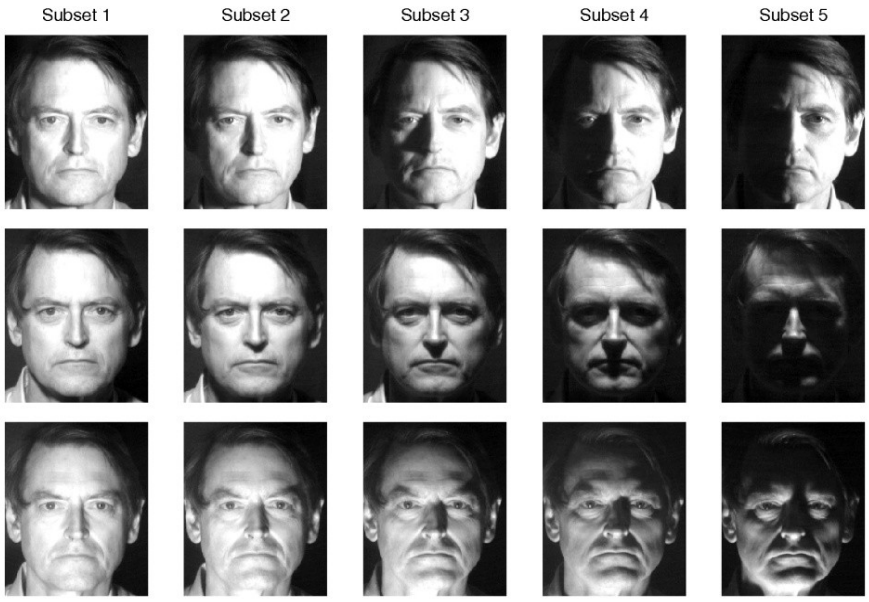


Figure 7: Face-patch changes under different illumination conditions. We can easily find how strong the illumination can affects the face appearance. [40]

Figure 8: Face-patch changes under different pose conditions. When the head pose changes, the spatial relation (distance, angle, etc.) among fiducial points (eyes, mouth, etc.) also changes and results in serious distortion on the traditional appearance representation. [41]

3.3Design issues

When designing a face detection and face recognition system, in addition to considering the aspects from psychophysics and neuroscience and the factors of human appearance variations, there are still some design issues to be taken into account.

First, the execution speed of the system reveals the possibility of on-line service and the ability to handle large amounts of data. Some previous methods could accurately detect human faces and determine their identities by complicated algorithms, which requires a few seconds to a few minutes for just an input image and can't be used in practical applications. For example, several types of digital cameras now have the function to detect and focus on human faces, and this detection process usually takes less than 0.5 second. In recent pattern recognition researches, lots of published papers concentrate their works on how to speed-up the existing algorithms and how to handle large amounts of data simultaneously, and new techniques also include the

execution time in the experimental results as comparison and judgment against other techniques.

Second, the training data size is another important issue in algorithm design. It is trivial that more data are included, more information we can exploit and better performance we can achieve. While in practical cases, the database size is usually limited due to the difficulty in data acquisition and the human privacy. Under the condition of limited data size, the designed algorithm should not only capture information from training data but also include some prior knowledge or try to predict and interpolate the missing and unseen data. In the comparison between the eigenface and the fisherface, it has been examined that under limited data size, the eigenface has better performance than the fisherface.

Finally, how to bring the algorithms into uncontrolled conditions is yet an unsolved problem. In Section 3.2, we have mentioned six types of appearance-variant factors, in our knowledge until now, there is still no technique simultaneously handling these factors well. For future researches, besides designing new algorithms, we'll try to combine the existing algorithms and modify the weights and relationship among them to see if face detection and recognition could be extended into uncontrolled conditions.

4. Face detection

From this section on, we start to talk about technical and algorithm aspects of face recognition. We follow the three-step procedure depicted in fig. 1 and introduce each step in the order: Face detection is introduced in this section, and feature extraction and face recognition are introduced in the next section. In the survey written by Yang et al. [7], face detection algorithms are classified into four categories: knowledge-based, feature invariant, template matching, and the appearance-based method. We follow their idea and describe each category and present excellent examples in the following subsections. To be noticed, there are generally two face detection cases, one is based on gray level images, and the other one is based on colored images.

4.1Knowledge-based methods

These rule-based methods encode human knowledge of what constitutes a typical face. Usually, the rules capture the relationships between facial features. These methods are designed mainly for face localization, which aims to determine the image position of a single face. In this subsection, we introduce two examples based on hierarchical knowledge-based method and vertical / horizontal projection.

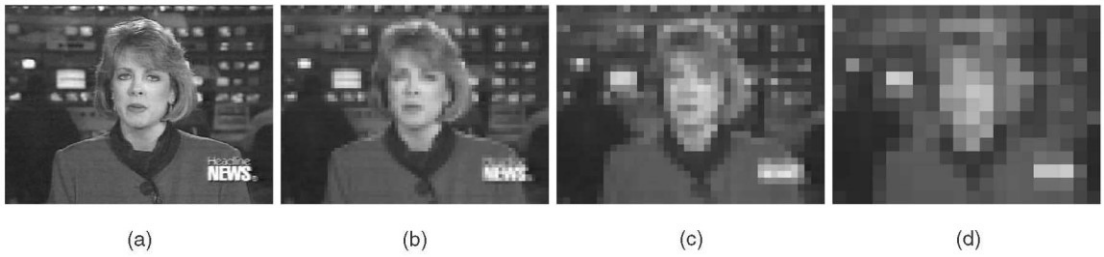


Figure 9: The multi-resolution hierarchy of images created by averaging and sub-sampling. (a) The original image. (b) The image with each 4-by-4 square substituted by the averaged intensity of pixels in that square. (c) The image with 8-by-8 square. (d) The image with 16-by-16 square. [7]

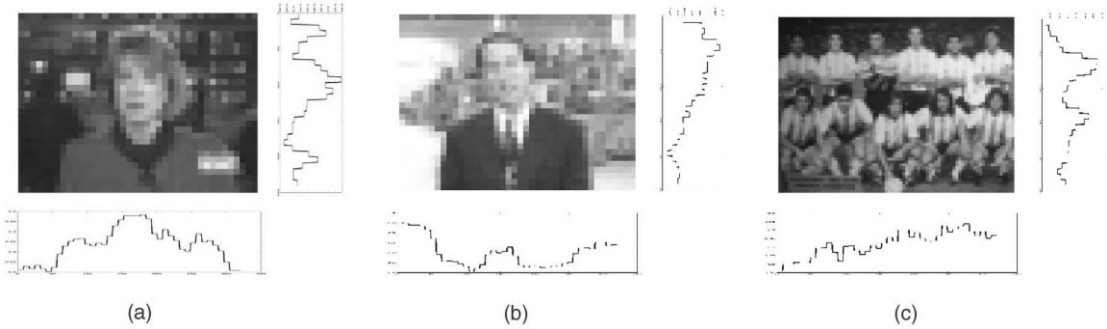


Figure 10: Examples of the horizontal / vertical projection method. The image (a) and image (b) are sub-sampled with 8-by-8 squares by the same method described in fig. 7, and (c) with 4-by-4. The projection method performs well in image (a) while can't handle complicated backgrounds and multi-face images in image (b) and (c). [7]

4.1.1 Hierarchical knowledge-based method

This method is composed of the multi-resolution hierarchy of images and specific rules defined at each image level [8]. The hierarchy is built by image sub-sampling and an example is shown in fig. 9. The face detection procedure starts from the highest layer in the hierarchy (with the lowest resolution) and extracts possible face candidates based on the general look of faces. Then the middle and bottom layers carry rule of more details such as the alignment of facial features and verify each face candidate. This method suffers from many factors described in Section 3 especially the RST variation and doesn't achieve high detection rate (50 true positives in 60 test images), while the coarse-to-fine strategy does reduces the required computation and is widely adopted by later algorithms.

4.1.2 Horizontal / vertical projection

This method uses the fairly simple image processing technique, the horizontal and vertical projection [9]. Based on the observations that human eyes and mouths have lower intensity than other parts of faces, these two projections are performed on the test image and local minimums are detected as facial feature candidates

which together constitute a face candidate. Finally, each face candidate is validated by further detection rules such as eyebrow and nostrils. As shown in fig. 10, this method is sensitive to complicated backgrounds and can't be used on images with multiple faces.

4.2Feature invariant approaches

These algorithms aim to find structural features that exist even when the pose, viewpoint, or lighting conditions vary, and then use these to locate faces. These methods are designed mainly for face localization. To distinguish from the knowledge-based methods, the feature invariant approaches start at feature extraction process and face candidates finding, and later verify each candidate by spatial relations among these features, while the knowledge-based methods usually exploit information of the whole image and are sensitive to complicated backgrounds and other factors described in Section 3. We present two characteristic techniques of this category in the following subsections, and readers could find more works in [6][12][13][14][26][27].

4.2.1 Face Detection Using Color Information

In this work, Hsu et al. [10] proposed to combine several features for face detection. They used color information for skin-color detection to extract candidate face regions. In order to deal with different illumination conditions, they extracted the 5% brightest pixels and used their mean color for lighting compensation. After skin-color detection and skin-region segmentation, they proposed to detect invariant facial features for region verification. Human eyes and mouths are selected as the most significant features of faces and two detection schemes are designed based on chrominance contrast and morphological operations, which are called "eyes map" and "mouth map". Finally, we form the triangle between two eyes and a mouth and verify it based on (1) luminance variations and average gradient orientations of eye and mouth blobs, (2) geometry and orientation of the triangle, and (3) the presence of a face boundary around the triangle. The regions pass the verification are denoted as faces and the Hough transform are performed to extract the best-fitting ellipse to extract each face.

This work gives a good example of how to combine several different techniques together in a cascade fashion. The lighting compensation process doesn't have a solid background, but it introduces the idea that despite modeling all kinds of illumination conditions based on complicated probability or classifier models, we can design an illumination-adaptive model which modifies its detection threshold based on the illumination and chrominance properties of the present image. The eyes map and

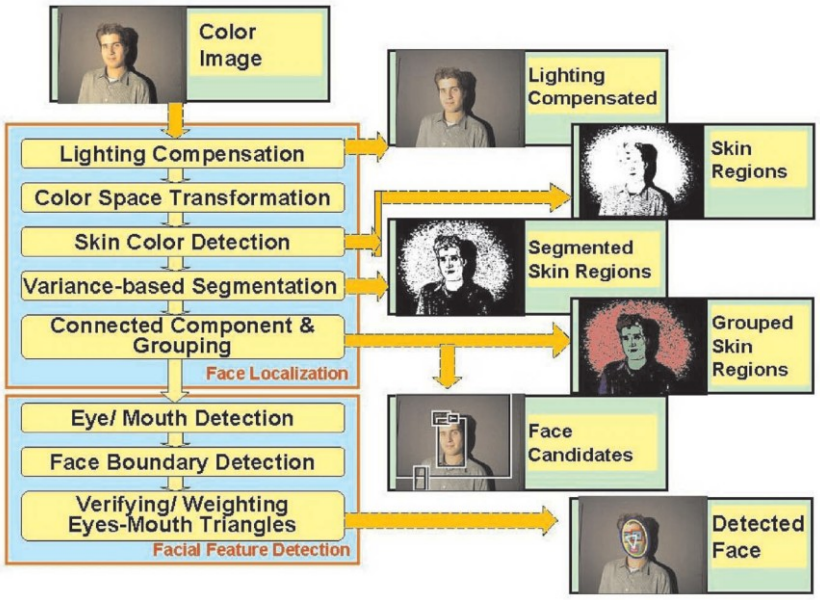


Figure 11: The flowchart of the face detection algorithm proposed by Hsu et al. [10]

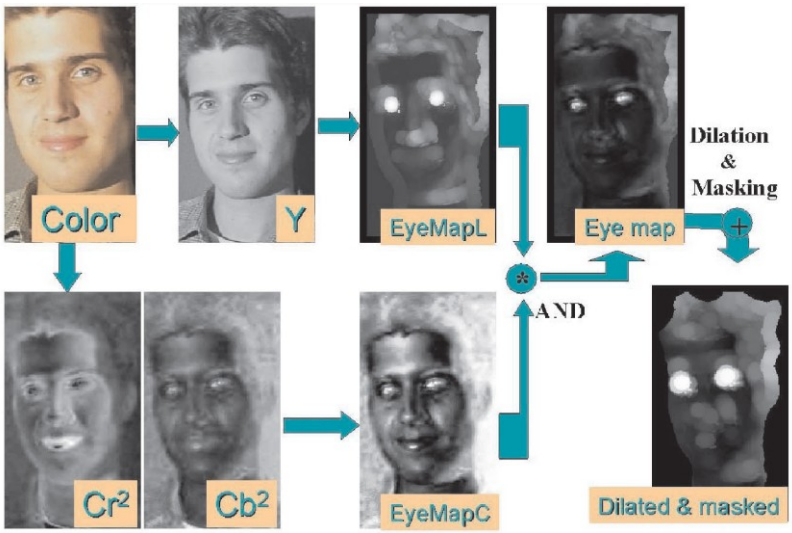


Figure 12: The flowchart to generate the eye map. [10]

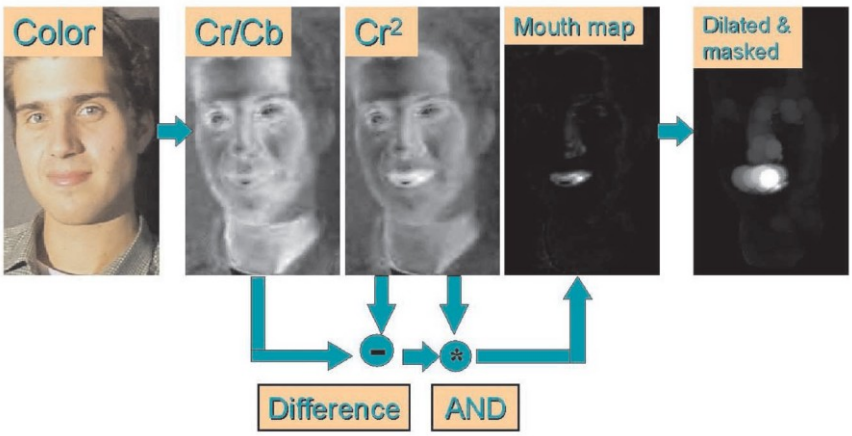


Figure 13: The flowchart to generate the mouth map. [10]

the mouth map shows great performance with fairly simple operations, and in our recent work we also adopt their framework and try to design more robust maps.

4.2.2 Face detection based on random labeled graph matching

Leung et al. developed a probabilistic method to locate a face in a cluttered scene based on local feature detectors and random graph matching [11]. Their motivation is to formulate the face localization problem as a search problem in which the goal is to find the arrangement of certain features that is most likely to be a face pattern. In the initial step, a set of local feature detectors is applied to the image to identify candidate locations for facial features, such as eyes, nose, and nostrils, since the feature detectors are not perfectly reliable, the spatial arrangement of the features must also be used for localize the face.

The facial feature detectors are built by the multi-orientation and multi-scale Gaussian derivative filters, where we select some characteristic facial features (two eyes, two nostrils, and nose/lip junction) and generate a prototype filter response for each of them. The same filter operation is applied to the input image and we compare the response with the prototype responses to detect possible facial features. To enhance the reliability of these detectors, the multivariate-Gaussian distribution is used to represent the distribution of the mutual distances among each facial feature, and this distribution is estimated by a set of training arrangements. The facial feature detectors averagely find 10-20 candidate locations for each facial feature, and the brute-force matching for each possible facial feature arrangement is computationally very demanding. To solve this problem, the authors proposed the idea of controlled search. They set a higher threshold for strong facial feature detection, and each pair of these strong features is selected to estimate the locations of other three facial features using a statistical model of mutual distances. Furthermore, the covariance of the estimates can be computed. Thus, the expected feature locations are estimated with high probability and shown as ellipse regions as depicted in fig. 14. Constellations are formed only from candidate facial features that lie inside the appropriate locations, and the ranking of constellation is based on a probability density function that a constellation corresponds to a face versus the probability it was generated by the non-face mechanism. In their experiments, this system is able to achieve a correct localization rate of 86% for cluttered images.

This work presents how to estimate the statistical properties among characteristic facial features and how to predict possible facial feature locations based on other observed facial features. Although the facial feature detectors used in this work is not robust compared to other detection algorithms, their controlled search scheme could detect faces even some features are occluded.

Figure 14: The locations of the missing features are estimated from two feature points. The ellipses show the areas which with high probability include the missing features. [11]

4.3Template matching methods

In this category, several standard patterns of a face are stored to describe the face as a whole or the facial feature separately. The correlations between an input image and the stored pattern are computed for detection. These methods have been used for both face localization and detection. The following subsection summarizes an excellent face detection technique based on deformable template matching, where the template of faces is deformable according to some defined rules and constraints.

4.3.1 Adaptive appearance model

In the traditional deformable template matching techniques [31], the deformation constraints are determined based on user-defined rules such as first- or second-order derivative properties [15]. These constraints are seeking for the smooth nature or some prior knowledge, while not all the patterns we are interested in have these properties. Furthermore, the traditional techniques are mainly used for shape or boundary matching, not for texture matching.

The active shape model (ASM) proposed by Kass et al. [16] exploits information from training data to generate the deformable constraints. They applied the principal component analysis (PCA) [17][18] to learn the possible variation of object shapes, and from their experimental results shown in fig. 15, we can see the most significant principal components are directly related to some factors of variation, such as length or width. Although the principal component analysis can't exactly capture the nonlinear shape variation such as bending, this model presents a significant way of thinking: learning the deformation constraints directly from the possible variation.

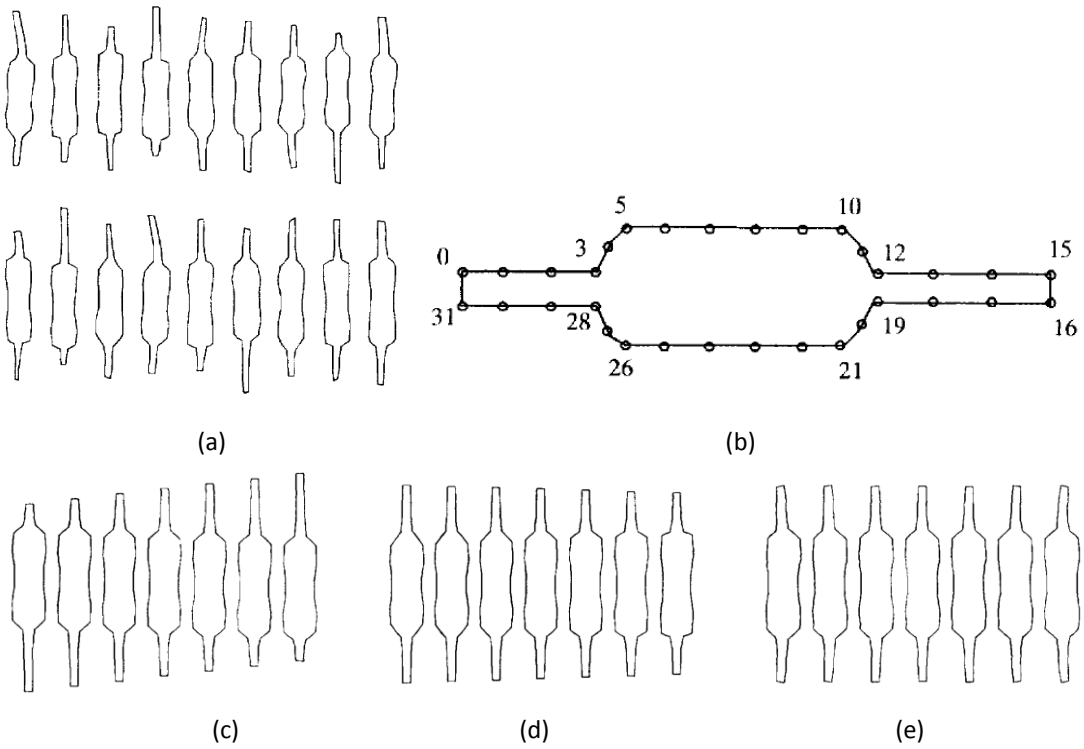


Figure 15: The example of the ASM for resistor shapes. In (a), the shape variation of resistors are summarized and several discrete points are extracted from the shape boundaries for shape learning, as shown in (b). From (c) to (e), the effects of changing the weight of the first three principal components are presented, and we can see the relationship between these components and the shape variation. [15]

The ASM model can only deal with shape variation but not texture variation. Following their works, there are many works trying to combine shape and texture variation together, for example, Edwards et al. proposed that first matching an ASM to boundary features in the image, then a separate eigenface model (texture model based on the PCA) is used to reconstruct the texture in a shape-normalized frame. This approach is not, however, guaranteed to give an optimal fit of the appearance (shape boundary and texture) model to the image because small errors in the match of the shape model can result in a shape-normalized texture map that can't be reconstructed correctly using eigenface model. To direct match shape and texture simultaneously, Cootes et al. proposed the well-know active appearance model (AAM) [19][20].

The active appearance model requires a training set of annotated images where corresponding points have been marked on each example. In fig. 16, we show that to build a facial model, the main features of human faces are required to be marked manually (each face image is marked as a vector x). The ASM is then applied to align these sets of points and build a statistical shape model. Based on the trained ASM,

each training face is warped so the points match those of the mean shape $\bar{x}$, obtaining a shape-free patch. These shape-free patches are further represented as a set of vectors and undergo the intensity normalization process (each vector is denoted as g). By applying the PCA to the intensity normalized data we obtain a linear model that captures the possible texture variation. We summarize the process that has been done until now for the AAM as follows:

$$x = \bar{x} + P_s b_s$$
$$g = \bar{g} + P_g b_g$$

, where P_s is the orthonormal bases of the ASM and b_s is the set of shape parameters for each training face. The matrix P_{g} is the orthonormal bases of the texture variation and b_{g} is the set of texture parameters for each intensity normalized shape-free patch. The details and process of the PCA is described in Section 5.

To capture the correlation between shape and texture variation, a further PCA is applied to the data as follows. For each training example we generate the concatenated vector:

$$b = \begin{pmatrix} W_s b_s \\ b_g \end{pmatrix} = \begin{pmatrix} W_s P_s^T (x - \bar{x}) \\ P_g^T (g - \bar{g}) \end{pmatrix}$$

, where W_s is a diagonal matrix of weights for each shape parameter, allowing for the difference in units between the shape and texture models. The PCA is applied on these vectors to generate a further model:

$$b = Qc$$

, where *Q* represents the eigenvectors and *c* is a vector of appearance parameters controlling both the shape and texture of the model. Note that the linear nature of the model allows us to express the shape and texture directly as function of *c*:

$$x = \bar{x} + P_s W_s Q_s c$$
$$g = \bar{g} + P_g Q_g c$$
$$Q = \begin{pmatrix} Q_s \\ Q_g \end{pmatrix}$$

An example image can be synthesized for a given *c* by generating the shape-free texture patch first and warp it to the suitable shape.

In the training phase for face detection, we learn the mean vectors of shape and texture, P_s, P_{g}, W_s, and *Q* to generate a facial AAM. And in the face detection phase,

we modify the vector *c*, the location and scale of the model to minimize the difference between synthesized appearance and the current location and scale in the input image. After reaching a local minimum difference, we compare it with a pre-defined threshold to determine the existence of a face. Fig. 17 illustrates the difference-minimization process. The parameter modification is rather a complicated optimization, and in their works, they combined the genetic algorithm and a pre-defined Parameter-refinement matrix to facilitate the convergence process. These techniques are beyond the scope of this report, and the readers who are interested in them can refer to the original papers [19].

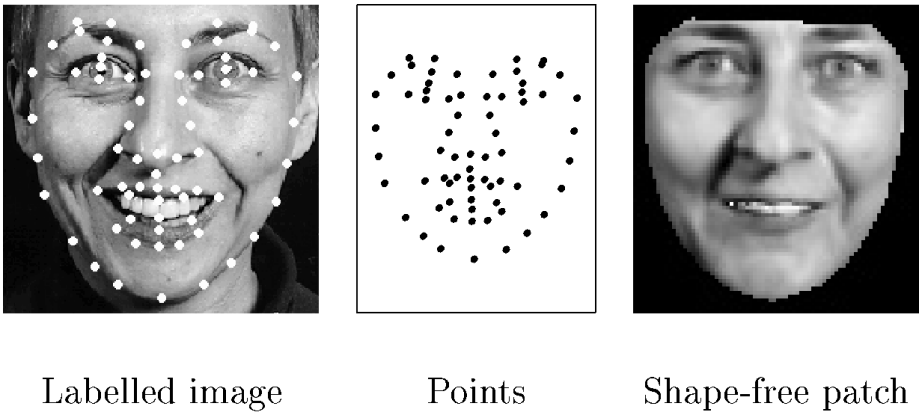


Figure 16: A labeled training image gives a shape free patch and a set of points. [19]

Figure 17: The fitting procedure of the adaptive appearance model after specific iterations. [19]

4.4 Appearance-based methods

In contrast to template matching, the models (or templates) are learned from a set of training images which should capture the representative variability of facial appearance. These learned models are then used for detection. These methods are designed mainly for face detection, and two high-cited works are introduced in the following sections. More significant techniques are included in [7][24][25][26].

4.4.1 Example-based learning for view-based human face detection

The appearance-based methods consider not the facial feature points but all regions of the face. Given a window size, the appearance-based method scans through the image and analyze each covered region. In the work of Sung et al. [21], the window size of 19x19 is selected for training and each extracted patch can be represented by a 381-dimensional vector, which is shown in fig. 18. A face mask is used to disregard pixels near the boundaries of the window which may contain background pixels, and reduce the vector into 283 dimensions. In order to better capture the distribution of the face samples, the Gaussian mixture model [28] is used. Given samples of face patches and non-face patches, two six-component Gaussian mixture models are trained based on the modified *K*-means algorithm [28]. The non-face patches need to be carefully chosen in order to include non-face samples as many as possible, especially some naturally non-face patterns in the real world that look like faces when viewed in a selected window. To classify a test patch, the distances between the patch and the 12 trained components are extracted as the patch feature, and a multilayer neural network [29][30] is trained to capture the relationship between these patch features and the corresponding labels.

During the face detection phase, several window sizes are selected to scan the input image, where each extracted patches are first resized into size of 19x19. Then we perform the mask operation, extract the patch features, and classify each patch into face or non-face based on the neural network classifier.

4.4.2 Fast face detection based on the Haar features and the Adaboost algorithm

The appearance-based method usually has better performance than the feature-invariant because it scans all the possible locations and scales in the image, but this exhaustive searching procedure also result in considerable computation. In order to facilitate this procedure, Viola et al. [22][23] proposed the combination of the Haar features and the Adaboost classifier [18][28]. The Haar features are used to capture the significant characteristics of human faces, especially the contrast features. Fig. 19 shows the adopted four feature shapes, where each feature is labeled by its width, length, type, and the contrast value (which is calculated as the averaged

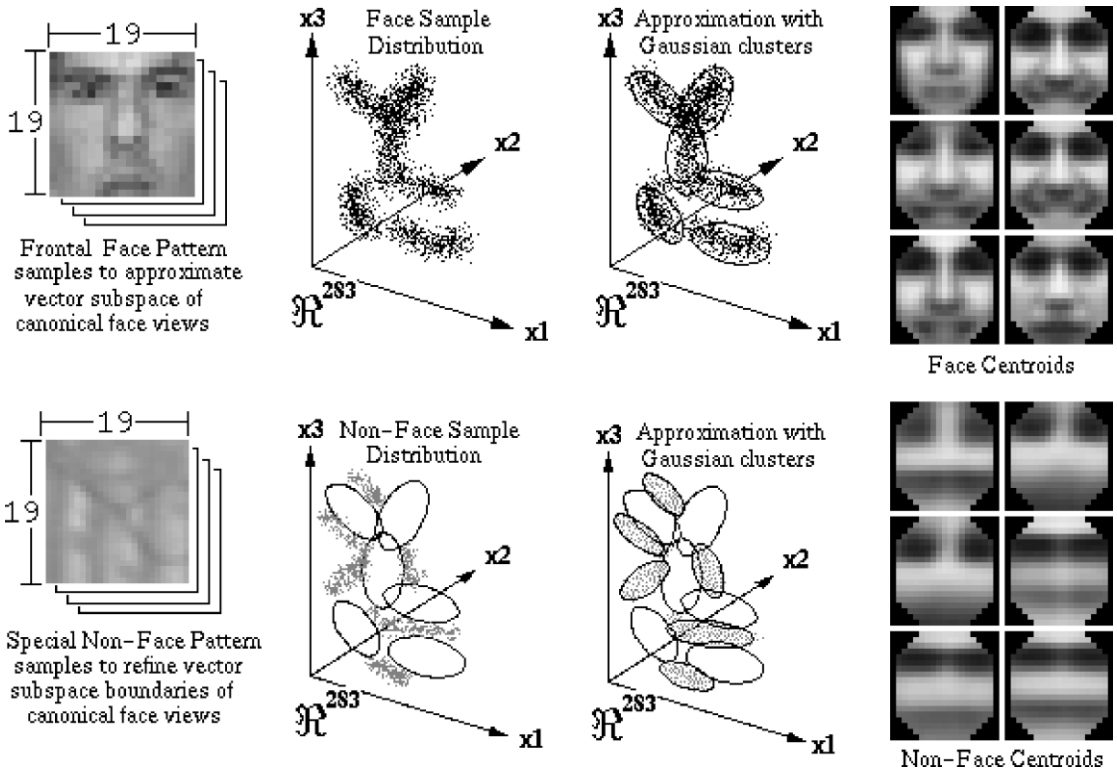


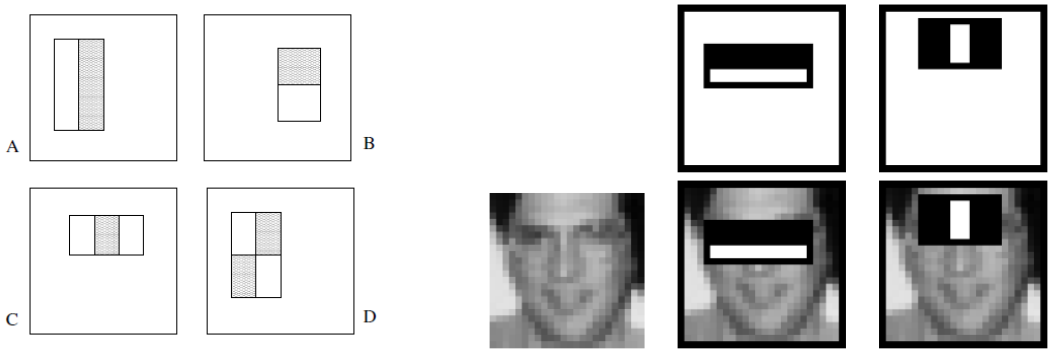
Figure 18: The modeling procedure of the distribution of face and non-face samples. The window size of 19x19 is sued for representing the canonical human frontal face. In the top row, a six-component Gaussian mixture model is trained to capture the distribution of face samples; while in the bottom row a six-component model is trained for non-face samples. The centroids of each component are shown in the right side of the figure. [21]

intensity in the black region minus the averaged intensity in the white region). A 19x19 window typically contains more than one thousand Haar features and results in huge computational cost, while many of them don't contribute to the classification between face and non-face samples because both face and non-face samples have these contrasts. To efficiently apply the large amount of Haar features, the Adaboost algorithm is used to perform the feature selection procedure and only those features with higher discriminant abilities are chosen. Fig. 19 also shows two significant Haar features which have the highest discriminant abilities. For further speedup, the chosen features are utilized in a cascade fashion, where the features with higher discriminant abilities are tested at the first few stages and the image windows passing these tests are fed into the later stages for detailed tests. The cascade procedure could quickly filter out many non-face regions by testing only a few features at each stage and shows significant computation saving.

The key concept of using the cascade procedure is to keep sufficient high true positive rate at each stage, and this could be reached by modifying the threshold of the classifier at each stage. Although modifying the threshold to reach high true positive

rate will also increases the false positive rate, this effect could be attenuated by the cascade procedure. For example, a classifier with 99% true positive rate and 20% false positive rate is not sufficient for practical use, while cascading this performance for three times could result in 95% true positive rate while 0.032% false positive rate, which is surprisedly improved. During the training phase of the cascade procedure, we set a lower bound of true positive rate and a higher bound of false positive rate for each stage and the whole system. We train each stage in term to achieve the desired bound, and increase a new stage if the bound of the whole system hasn't been reached.

In the face detection phase, several window scales and locations are chosen to extract possible face patches in the image, and we test each patch by the trained cascade procedure and those which pass all the stages are labeled as faces. There are many works later based on their framework, such as [32].



(a) (b)

Figure 19: The Haar features and their abilities to capture the significant contrast feature of the human face. [23]

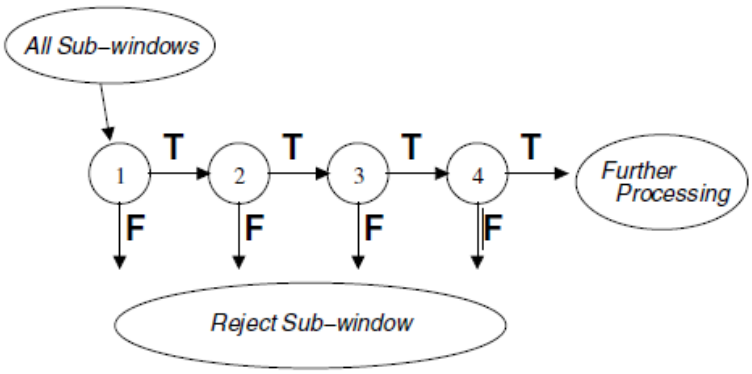


Figure 20: The cascade procedure during the training phase. At each stage, only a portion of patches can be denoted as faces and pass to the following stage for further verifications. The patches denoted as non-face at each stage are directly rejected. [23]

4.5 Part-based methods

With the development of the graphical model framework [33] and the point of interest detection such as the difference of Gaussian detector [34] (used in the SIFT detector) and the Hessian affine detector [35], the part-based method recently attracts more attention. We'd like to introduce two outstanding examples, one is based on the generative model and one is based on the support vector machine (SVM) classifier.

4.5.1 Face detection based on the generative model framework

R. Fergus et al. [36] proposed to learn and recognize the object models from unlabeled and unsegmented cluttered scenes in a scale invariant manner. Objects are modeled as flexible constellations of parts, and only the topic of each image should be given (for example, car, people, or motors, etc.). The object model is generated by the probabilistic representation and each object is denoted by the parts detected by the entropy-based feature detector. Aspects including appearances, scales, shapes, and occlusions of each part and the object are considered and modeled by the probabilistic representation to deal with possible object variances.

Given an image, the entropy-based feature detector is first applied to detect the top *P* parts (including locations and scales) with the largest entropies, and then these parts are fed into the probabilistic model for object recognition. The probabilistic object model is composed of *N* interesting parts (*N*<*P*) and denoted as follows:

$$R = \frac{p(\text{Object} \mid X, S, A)}{p(\text{No object} \mid X, S, A)} = \frac{p(X, S, A \mid \text{Object})\, p(\text{Object})}{p(X, S, A \mid \text{No object})\, p(\text{No object})} \approx \frac{p(X, S, A \mid \theta)\, p(\text{Object})}{p(X, S, A \mid \theta_{bg})\, p(\text{No object})}$$

$$p(X, S, A \mid \theta) = \sum_{h \in H} p(X, S, A, h \mid \theta) = \sum_{h \in H} \underbrace{\qquad}_{\text{Appearance}} \underbrace{\qquad}_{\text{Shape}} \underbrace{\qquad}_{\text{Ref. scale}} \underbrace{\qquad}_{\text{Other}}$$

, where *X* denotes the part locations, *S* denotes the scales, and *A* denotes the appearances. The indexing variable *h* is a hypothesis to determine the attribute of each detected part (belong to the *N* interesting parts of the object or not) and the possible occlusion of each interesting part (If no detected part is assigned to an interesting part, this interesting part is occluded in the image). Note that *P* regions are detected from the image while we assume that only *N* points are characteristics of the object and other parts belong to the background.

The model is trained by the well-known expectation maximization (EM) algorithm [28] in order to cope with the unobserved variable *h*, and both the object model and background model are trained from the same set of object-labeled images. Then when an input image comes in, we first extract its *P* parts and calculate the quantity *R*. Comparing this *R* with a defined threshold, we can determine if there is any face appears in the image. In addition to this determination, we can analyze each *h* and extract the *N* interesting parts of this image according to *h* with the highest probability score. From fig. 21, we see that these detected *N* parts based on the highest score *h* actually capture the meaningful characteristics of human faces.

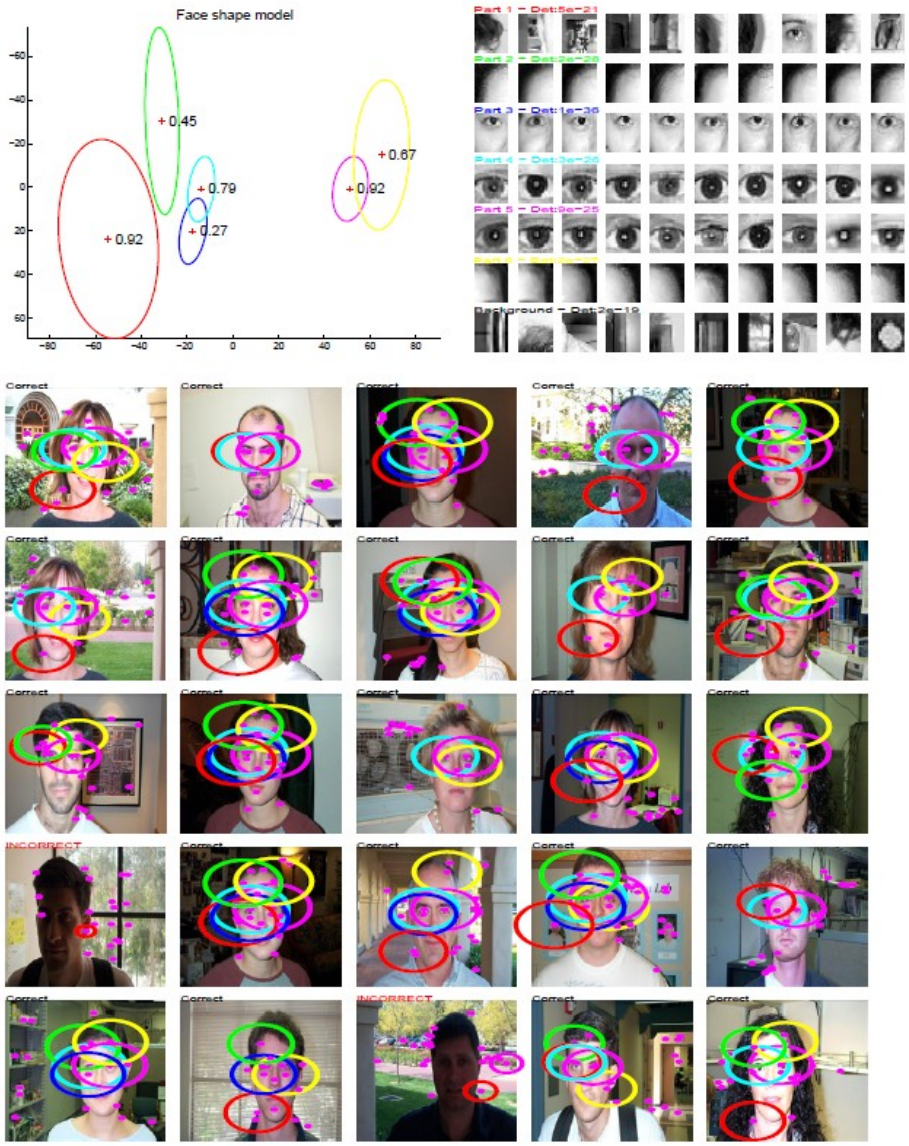


Figure 21: An example of face detection based on the generative model framework. (Up-left) The averaged location and the location variance of each interesting part of the face. (Up-right) Sample appearances of the six interesting parts and the background part (the bottom row). (Bottom) Examples of faces and the corresponding interesting parts. [36]

4.5.2 Component-based face detection based on the SVM classifier

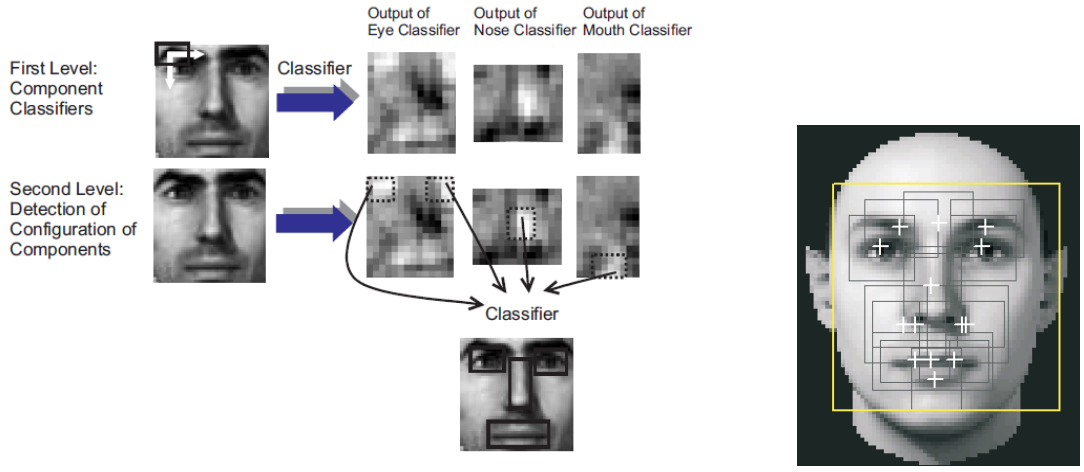
Based on the same idea of using detected parts to represent human faces, Bernd et al. [37] proposed the face detection algorithm consisting of a two-level hierarchy of support vector machine (SVM) classifiers [18][28]. On the first level, component classifiers independently detect components of a face. On the second level, a single classifier checks if the geometrical configuration of the detected components in the image matches a geometrical model of a face. Fig. 22 shows the procedure of their algorithm.

On the first level, the linear SVM classifiers are trained to detect each component. Rather than manually extracting each component from training images, the authors proposed an automatic algorithm to select components based on their discriminative power and their robustness against pose and illumination changes (in their implementation, 14 components are used). This algorithm starts with a small rectangular component located around a pre-selected point in the face. In order to simplify the training phase, the authors used synthetic 3D images for component learning. The component is extracted from all synthetic face images to build a training set of positive examples, and a training set of non-face pattern that have that same rectangular shape is also generated. After training an SVM on the component data, they estimate the performance of the SVM based on the estimated upper bound ρ on the expected probability of error and later the component is enlarged by expanding the rectangle by one pixel into one of the four directions (up, down, left, right). Again, they generated training data, trained an SVM, determined ρ, and finally kept the expansion which decreases ρ the most. This process is continued until the expansions into all four directions lead to an increase in ρ, and the SVM classifier of the component is determined.

On the second level the geometrical configuration classifier performs the final face detection by linear combining the results of the component classifiers. Given a 58×58 window (a current face searching window), the maximum continuous outputs of the component classifiers within rectangular search regions around the expected positions of the components and the detected positions are used as inputs to the geometrical configuration classifier. The search regions have been calculated from the mean and standard deviation of the locations of the components in the training images. The output of this second-level SVM tells us if a face is detected in the current 58×58 window. To search all possible scales and locations inside an input image, we need to change the window sizes of each component and possible face size, which is an exhaustive process.

In their work, they proposed three basic ideas behind part- or component-based detection of objects. First, some object classes can be described well by a few cha-

racteristic object parts and their geometrical relation. Second, the patterns of some object parts might vary less under pose changes than the pattern belonging to the whole object. Third, a component-based approach might be more robust against partial occlusions than a global approach. And the two main problems of a component-based approach are how to choose the set of discriminatory object parts and how to model their geometrical configuration.



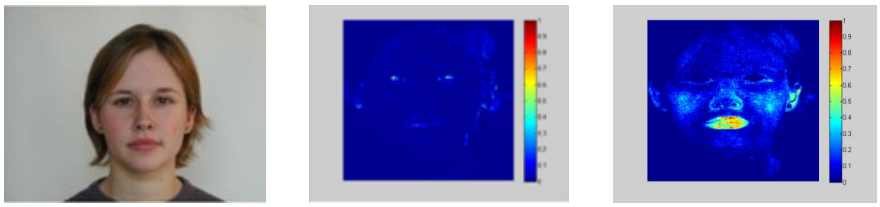
(a) (b)

Fig 22: In (a), the system overview of the component-based classifier using four components is presented. On the first level, windows of the size of the components (solid line boxes) are shifted over the face image and classified by the component classifiers. On the second, the maximum outputs of the component classifiers within predefined search regions (dotted lined boxes) and the positions of the components are fed into the geometrical configuration classifier. In (b), the fourteen learned components are denoted by the black boxes with the corresponding center marked by crosses. [37]

4.6 Our proposed methods

(a) (b)

Figure 23: (a) The input image and the result after skin-color detection. (b) The extracted connected patch and its most fitted ellipse.



(a) (b)

Figure 24: The results after (a) the eyes map (b) and the mouth map.

In our previous work [37], we adopt the top-down method to detect faces in an image. We first classify pixels into skin color or non-skin color, and then find candidate face regions based on connected component algorithm. We discard small regions with fewer skin-color pixels, and verify the remained regions based on the most fitted ellipse. Regions have higher overlapping with its fitted ellipse are remained for further verification. Important and invariant facial features (ex. Eyes and mouths) are extracted from each candidate face region, and we test the relation among these feature points as well as their constellation and orientation against the face region. Finally, those candidate regions pass our heuristic testing procedure are determined as detected faces.

Our method suffers from the **hard decisions** between each block shown in fig. 25. Each block discards parts of the candidate regions, while these regions may have positive responses in the later blocks. Besides, our face detection relies on the well-defined skin color classification and facial feature extraction detection, which may not work well in complicated scenes. To solve these problems, we'd like to make these blocks parallel or exploit more robust features for detection.

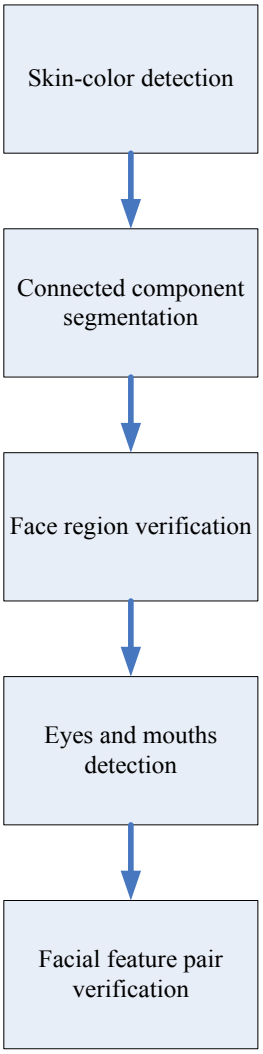
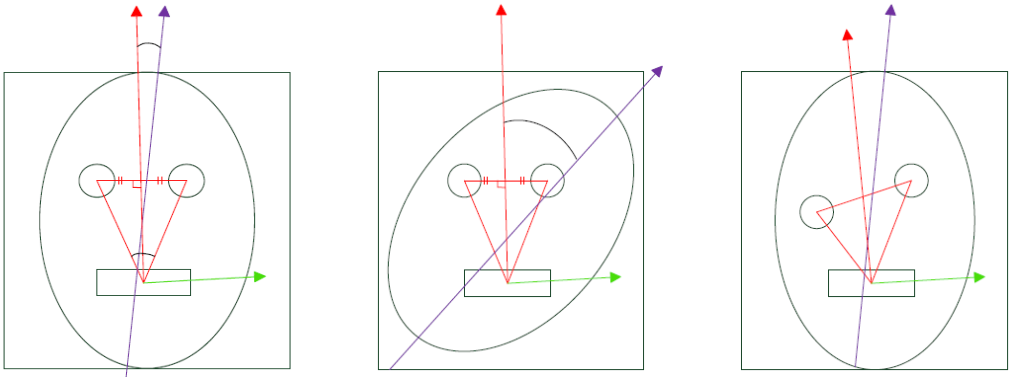


Figure 25: The procedure of our previous work



(a) (b) (c)

Figure 26: The facial feature pair verification process. In (a) we show an positive pair and (b-c) are two negative pairs. [37]

5. Feature Extraction and Face Recognition

Assumed that the face of a person is located, segmented from the image, and aligned into a face patch, in this section, we'll talk about how to extract useful and compact features from face patches. The reason to combine feature extraction and face recognition steps together is that sometimes the type of classifier is corresponded to the specific features adopted. In this section, we separate the feature extraction techniques into four categories: holistic-based method, feature-based method, template-based method, and part-based method. The first three categories are frequently discussed in literatures, while the forth category is a new idea used in recent computer vision and object recognition.

5.1Holistic-based methods

Holistic-based methods are also called appearance-based methods, which mean we use whole information of a face patch and perform some transformation on this patch to get a compact representation for recognition. To be more clearly distinguished from feature-based methods, we can say that feature-based methods directly extract information from some detected fiducial points (such as eyes, noses, and lips, etc. These fiducial points are usually determined from domain knowledge) and discard other information; while appearance-based methods perform transformations on the whole patch and reach the feature vectors, and these transformation basis are usually obtained from statistics.

During the past twenty years, holistic-based methods attract the most attention against other methods, so we will focus more on this category. In the following subsections, we will talk about the famous eigenface [39] (performed by the PCA), fisherface (performed by the LDA), and some other transformation basis such as the independent component analysis (ICA), nonlinear dimension reduction technique, and the over-complete database (based on compressive sensing). More interesting techniques could be found in [42][43].

5.1.1 Eigenface and Principal Component Analysis

The idea of eigenface is rather easy. Given a face data set (say *N* faces), we first scale each face patch into a constant size (for example, 100x100) and transfer each patch into vector representation (100-by-100 matrix into 10000-by-1 vector). Based on these *N* *D*-dimensional vectors (*D*=10000 in this case), we can apply the principal component analysis (PCA) [17][18] to obtain suitable basis (each is a *D*-dimensional vector) for dimension reduction. Assume we choose *M* projection basis ($M \ll D$),

each *D*-dimensional vector could be transformed into an *M*-dimensional vector representation. Generally, these *M* projection basis are called eigenfaces. The algorithms for PCA and eigenfaces representation are shown below:

Eigenface representation:

(1) Initial setting:

Originally *N D*-dimensional vectors: $\{\mathbf{x}_i\}_{i=1}^{N} \in \mathcal{R}^D$

A set of *M* projection basis: $\{\mathbf{u}_\mathrm{i}\}_{i=1}^{M} \in \mathcal{R}^D$

These basis are mutually orthogonal, and generally we have $M \ll D$

(2) The eigenface representation

For each $\mathbf{x}_i$ (*i*=1~*N*), we compute its projection onto $\{\mathbf{u}_\mathrm{i}\}_{i=1}^{M} \in \mathcal{R}^D$, and we can get a new M-dimensional vector $\mathbf{y}_i$. This process achieves our goal of dimension reduction.

The PCA basis:

PCA projection basis are purely data-driven, which are computed from the dataset we have. This projection process is also called Karhunen-Loeve transform in the data compression community. Given *N D*-dimensional vectors (In face recognition task, usually $N < D$), we can get at least min(*N*-1, *D*-1) projection basis with one mean vector:

(1) Compute the mean vector Ψ (*D*-by-1 vector)

(2) Subtract each $\mathbf{x}_i$ by Ψ and get Φ_i

(3) Calculate the covariance matrix Σ of all the Φ_is (*D*-by-*D* matrix)

(4) Calculate the set of Σ (*D*-by-(N-1) matrix, where each eigenvector is aligned as a column vector)

(5) Preserve the *M* largest eigenvectors based on their eigenvalues (*D*-by-*M* matrix *U*)

(6) $U^T\Phi_i$ is the eigenface representation (*M*-dimensional vector) of the *i*th face

The orthogonal PCA bases are proved to preserve the most projection energy and preserve the largest variation after projection, while the proof is not included in this report. In the work proposed by Turk et al., they proposed a speed-up algorithm to reach the eigenvectors form the covariance matrix Σ, and used the vectors after dimension reduction for face detection and face recognition. They also proposed some criteria for face detection and face tracking.

The PCA method has been proved to discard noise and outlier data from the training set, while they may also ignore some key discriminative factors which may not have large variation but dominate our perception. We'll compare this effect in the next subsection about the fisherface and linear discriminant analysis. To be announced, the eigenface algorithm did give significant influences on the algorithm design for holistic-based face recognition in the past twenty years, so it is a great starting point for readers to try building a face recognition system.

(a)

(b)

(c)

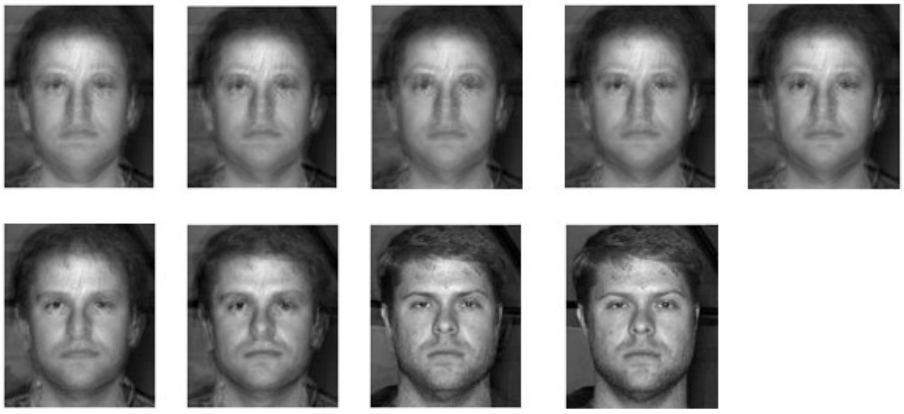
Figure 27: (a) We generate a database with only 10 faces and each face patch is of size 100-by-100. Through the computation of PCA basis, we get (b) a mean face and (c) 9 eigenface (the order of eigenfaces from highest eigenvalues is listed from left to right, and from top to bottom).

5.1.2 Fisherface and linear Discriminative Analysis

The eigenfaces have the advantage of dimension reduction as well as saving the most energy and the largest variation after projection, while they do not exploit the information of face label included in the database. Besides, there have been several researches showing that the illumination differences result in serious appearance variations, which means that first several eigenfaces may capture the variation of illumination of faces rather than the face structure variations, and some detailed structured difference may have small eigenvalues and their corresponding eigenfaces are probably dropped when only preserving the *M* largest eigenvectors.

Despite calculating the projection bases from the whole training data without labels (without human identities, which corresponds to unsupervised learning), Belhumeur et al. [40] proposed to use the linear discriminative analysis (LDA) [17] for bases finding. The objective of applying the LDA is to look for dimension reduction based on discrimination purpose as well as to find bases for projection that minimize the intra-class variation but preserve the inter-class variation. They didn't explicitly build the intra-class variation model, but linearly projected the image into a subspace

(a)



(b)

Figure 28: The reconstruction process based on eigenface representation. (a) The original face in the database could be reconstructed by its eigenface representation and the set of projection vectors (lossless if we use all PCA projection vectors, or this reconstruction will be lossy). (b) The reconstruction process with different number of basis used: From left to right, and from top to bottom, we in turn add one projection vector with its corresponding projection value. The bottom right picture using 9 projection vectors and the mean vector is the perfect reconstruction result.

in a manner which discounts those regions of the face with large intra-class deviation. Fig. 29 shows the difference of applying the PCA and LDA on the same labeled training data. The circled data point indicates the samples from class 1 and crossed from class 2, as you can see, the PCA basis preserved the largest variation after projection, while the projection result is not suitable for recognition. On the other hand, the LDA exploits the best projection basis for discrimination purpose, although it doesn't preserve as much energy as what the PCA does, the projection result clearly separates these two classes by just a simple thresholding. Fig. 30 also depicts the importance of choosing suitable projection bases.

In the two class problem, the LDA is also called the Fisher linear discriminant algorithm. Given a training set with 2 classes where D_i indicates the set of class i, we want to maximize the ratio of the inter-class variation to the intra-class variation as shown below:

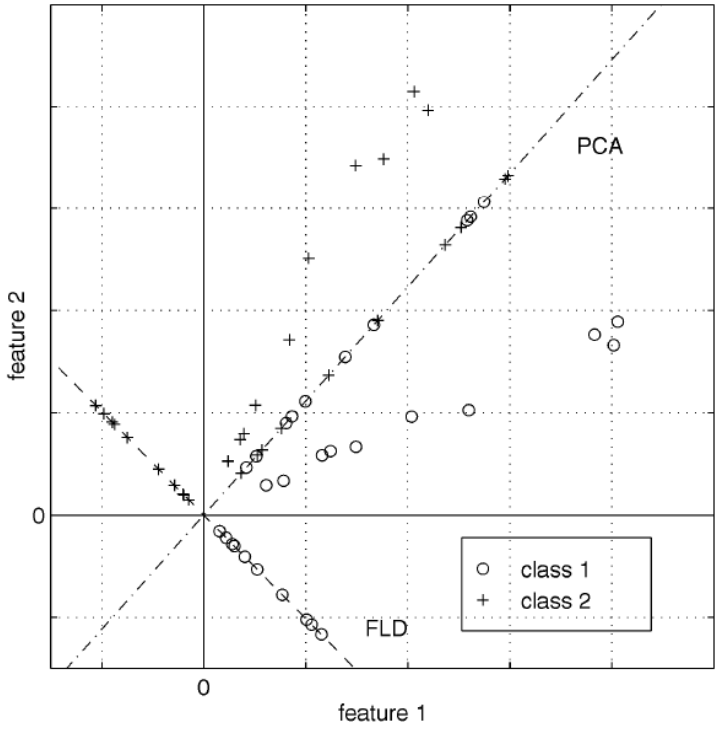


Figure 29: The comparison between Fisher linear discrimination and principal component analysis. [40]

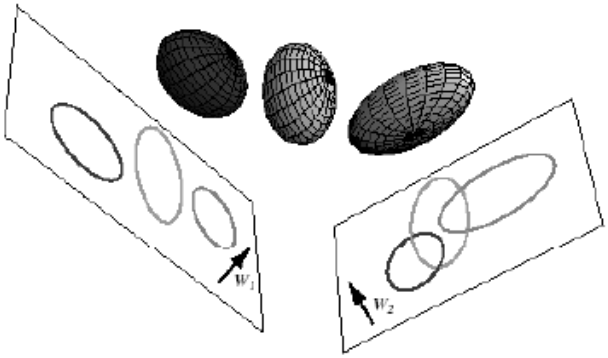


Figure 30: The figure of using different bases for projection. With suitable bases, the dimension-reduced result could preserve the discriminative nature of the original data. [17]

$$\text{inter-class: } |\tilde{\imath} \quad \tilde{} \qquad n_1 - m_2)|$$

$$\text{intra-class: } \tilde{} \qquad \tilde{} \qquad y \in Y_i$$

$$\text{want to maximize: } J(w) = \frac{|\tilde{\imath}}{\tilde{} \quad \tilde{}}$$

, where y is the projected vector of the original sample x, and m_i, $\tilde{\imath}$ are the mean vectors of the original samples and projected samples in class i. The right side of the equation $J(w)$ could be further rewritten as follows:

$$\tilde{s} \quad {}_{x\in D_i} \; {}^{\mathrm{T}}x - w^{\mathrm{T}}m_i)(w^{\mathrm{T}}x - w^{\mathrm{T}}m_i)^{\mathrm{T}} = \sum_{x\in D_i} w^{\mathrm{T}}(x-m_i)(x-m_i)^{\mathrm{T}}w = w^{\mathrm{T}}S_i w$$

$$\tilde{s} \quad \tilde{} \quad \nu + w^{\mathrm{T}}S_2 w = w^{\mathrm{T}}S_{\mathrm{w}}w$$

$$|\tilde{r} \quad \tilde{} \quad m_1 - w^{\mathrm{T}}m_2)^2 = w^{\mathrm{T}}(m_1-m_2)(m_1-m_2)^{\mathrm{T}}w = w^{\mathrm{T}}S_{\mathrm{B}}w$$

$$\text{want to maximize: } J(w) = \frac{w^{\mathrm{T}}S_{\mathrm{B}}w}{w^{\mathrm{T}}S_{\mathrm{w}}w}$$

, where the w means the projection vector here to be calculated and D_i is the training set of class i. This obtained $J(w)$ is well known in mathematical physics as the generalized Rayleigh quotient, and a vector w that maximizes $J(w)$ must satisfy

$$S_{\mathrm{B}}w = \lambda S_{\mathrm{w}}w$$

for some constant λ, which is a generalized eigenvalues problem. If the S_{w} is nonsingular we can obtain a conventional eigenvalues problem by writing:

$$S_{\mathrm{w}}{}^{-1}S_{\mathrm{B}}w = \lambda w$$

And if S_{w} is nonsingular, we can choose either pre-reducing the dimensionality of x by the PCA or finding the bases from the nullspace of S_{w}.

To solve the multiclass problem, given a training set with *C* classes, the intra-class variation and inter-class variation could be rewritten as:

$$S_{\mathrm{B}} = \sum_{i=1}^{c} N_i(m_i - m)(m_i - m)^{\mathrm{T}}$$

$$S_{\mathrm{w}} = \sum_{i=1}^{c}\sum_{x\in D_i}(x-m_i)(x-m_i)^{\mathrm{T}}$$

$$\text{want to maximize: } J(W) = \frac{|W^{\mathrm{T}}S_{\mathrm{B}}W|}{|W^{\mathrm{T}}S_{\mathrm{w}}W|}$$

, where *m* is the mean vector of all the samples in the training set. *W* is the projection matrix where $W = [w_1\ w_2 \ldots\ldots w_{\mathrm{m}}]$ with $m \le c-1$, and each w_i should satisfy

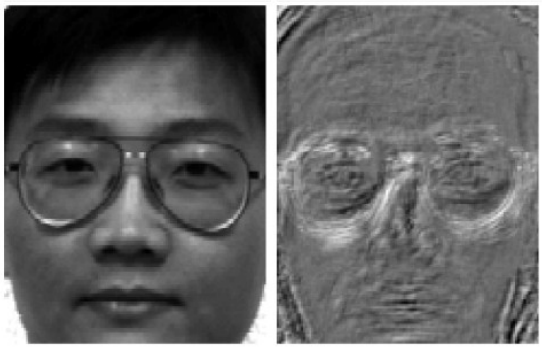
$$S_{\mathrm{B}}w_i = \lambda_i S_{\mathrm{w}}w_i$$

In order to deal with the singularity problem of S_{w}, Belhumeur et al. used the PCA method described as below, where all the samples x in the training data are first projected to an dimension-reduced space, and S_{B}, S_{w}, and W are calculate in this space:

$$W_{\mathrm{PCA}} = \arg\ \max_{W} |W^{\mathrm{T}}S_{\mathrm{T}}W| \ \text{ where } S_{\mathrm{T}} = \sum_{x}(x-m)(x-m)^{\mathrm{T}}$$

$$W_{\mathrm{FLD}} = \arg\ \max_{W} \frac{|W^{\mathrm{T}}W_{\mathrm{PCA}}{}^{\mathrm{T}}S_{\mathrm{B}}W_{\mathrm{PCA}}W|}{|W^{\mathrm{T}}W_{\mathrm{PCA}}{}^{\mathrm{T}}S_{\mathrm{w}}W_{\mathrm{PCA}}W|}$$

The S_w has the maximum rank as *N-C*, where *N* is the size of the training set, so we need to reduce the dimensionality of the samples x down to *N-C* or less. In their experiment results, the LDA bases outperform the PCA bases, especially in the illumination changing cases. The LDA could also be applied in other recognition cases. For example, fig.31 shows the projection basis for the glasses / without glasses case, and as you can see, this basis capture the glass shape around human eyes, rather than the face difference of people in the training set.



(a) (b)

Figure 31: The recognition case of human faces with glasses or without glasses. (a) an example of faces with glasses. (b) the projection basis reached by the LDA. [40]

5.1.3 Independent Component Analysis

Followed the projection and bases finding ideas, the following three subsections use different criteria to find the bases or decomposition of the training set. Because these criteria involve many mathematical and statistical theorems and backgrounds, here we will briefly describe the ideas behind them but no more details about the mathematical equation and theorems.

The PCA exploits the second-order statistical property of the training set (the covariance matrix) and yields projection bases that make the projected samples uncorrelated with each other. The second-order property only depends on the pair-wise relationships between pixels, while some important information for face recognition may be contained in the higher-order relationships among pixels. The independent component analysis (ICA) [18][31] is a generalization of the PCA, which is sensitive to the higher-order statistics. Fig. 32 shows the difference of the PCA bases and ICA bases.

In the works proposed by Bartlett et al. [44], they derived the ICA bases from the principle of optimal information transfer through sigmoidal neurons. In addition, they proposed to architectures for dimension-reduction decomposition, one treats the image as random variables and the pixels as outcomes, and the other one treats the

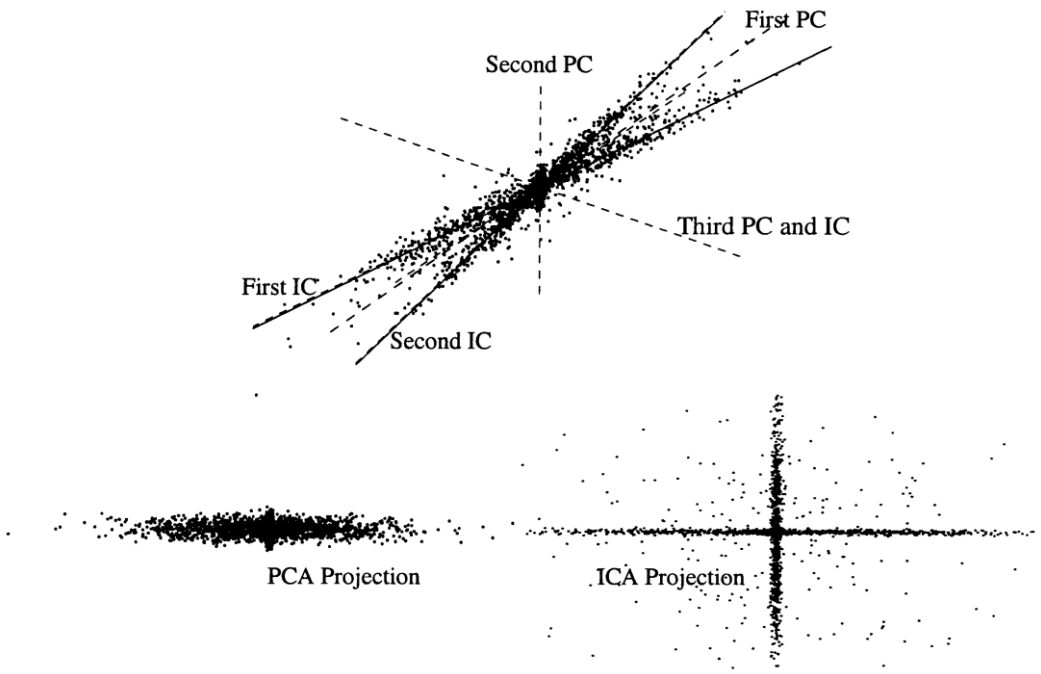


Figure 32: (top) Example 3-D data distribution and corresponding PC and IC axes. Each axis is a column of the projection matrix *W* found by the PCA and the ICA. Note that PC axes are orthogonal while the ICA axes are not. IF only two components are allowed, the ICA choose a different subspace than ICA. (bottom left) Distribution of the first PCA coordinates of the data. (bottom right) Distribution if the first ICA coordinates of the data. Note that since the ICA axes are non-orthogonal, relative distance between points are different in the PCA than in the ICA, as are the angels between points. As you can see, the bases found by ICA preserve more original structure than the PCA. [44]

pixels as random variables and the image as outcomes. The Architecture I depicted in fig. 33 found *n* "source of pixel" images, where each has the appearance as shown in the column *U* illustrated in fig. 34, and a human face could be decomposed in to a weight vector as in fig. 35. This architecture finds a set of statistically independent basis images and each of them captures the features in human faces such as eyes, eyebrows, and mouths.

The Architecture II finds the basis images which have similar appearances as the PCA does as shown in fig. 36, and has the decomposition as shown in fig. 37. This architecture uses the ICA to find a representation in which the coefficients used to code images are statistically independent. Generally speaking, the first architectural finds spatially local basis images for the face, while the second architecture produces a factorial face code. In their experimental results, both these two representation were superior to the representation based on the PCA for recognizing faces across days and changes in expression, and a classifier combining these two ICA representation gave the best performance.

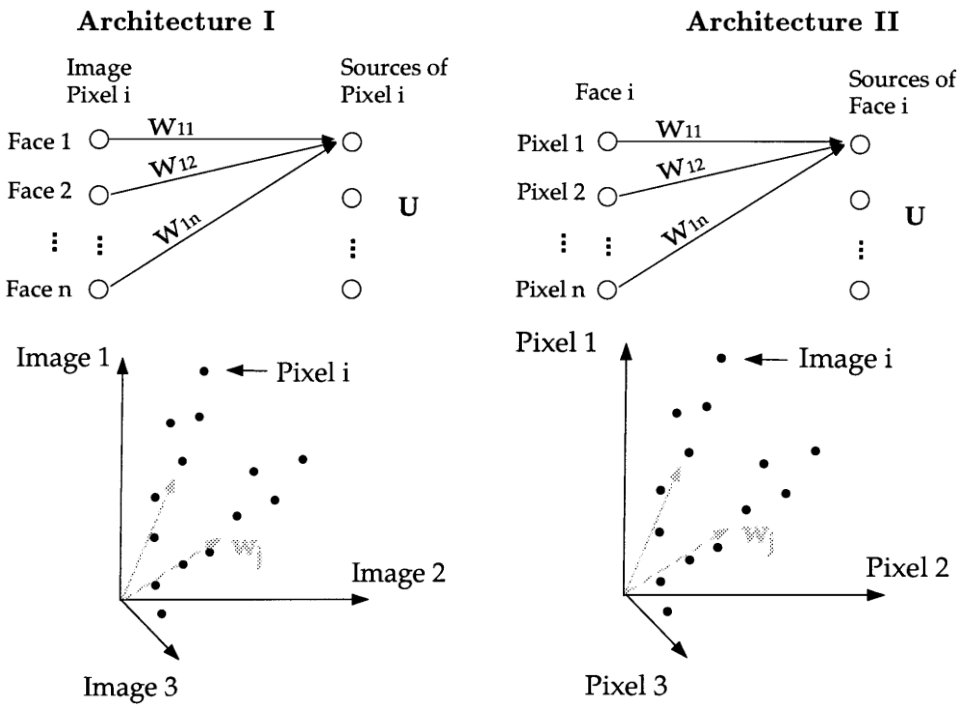


Figure 33: Two architectures for performing the ICA on images. (a) The Architecture I for finding statistically independent basis images. Performing source separation on the face images produced IC images in the rows of *U*. (b) The gray values at pixel location *I* are plotted for each face image. ICA in the Architecture I finds weight vectors in the directions of statistical dependencies among the pixel locations. (c) The Architecture II for finding a factorial code. Performing source separation on the pixels produced a factorial code in the columns of the output matrix, *U*. (d) Each face image is plotted according to the gray values taken on at each pixel location. The ICA in the Architecture II finds weight vectors in the directions of statistical dependencies among the face images. [44]

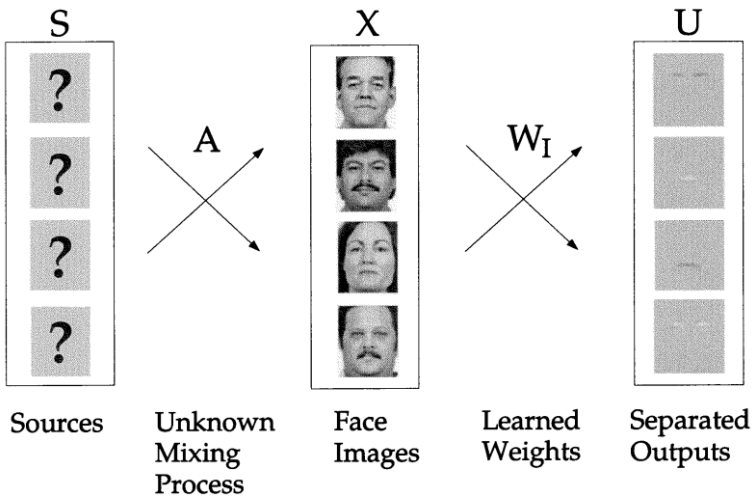
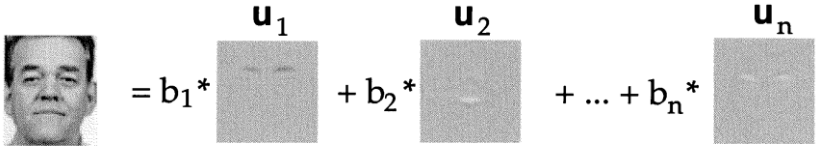


Figure 34: Image synthesis model for the Architecture I. To find a set of IC images, the image in *X* are considered to be a linear combination of statistically independent basis images, *S*, where *A* is an unknown mixing matrix. The basis images were estimated as the learned ICA output *U*. [44]



ICA representation = ($b_1, b_2, \ldots, b_n$)

Figure 35: The independent basis image representation consisted of the coefficients, **b**, for the linear combination if independent basis images, **u**, that comprised each face image *x*. [44]

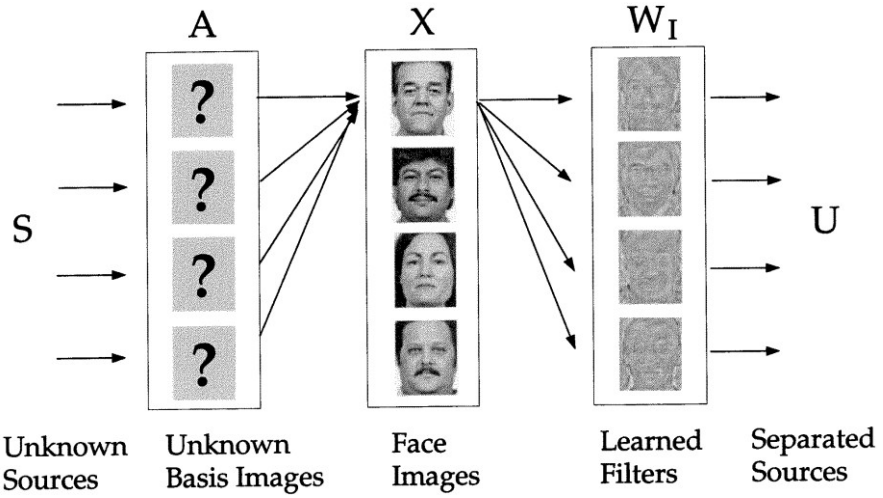
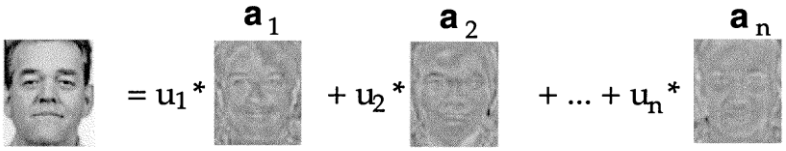


Figure 36: Image synthesis model for the Architecture II. Each image in the dataset was considered to be a linear combination if underlying basis images in the matrix *A*. The basis images were each associated with a set of independent "causes," given by a vector of coefficients *S*. The basis images were estimated by $A = W_I^{-1}$, where W is the learned ICA weight matrix. [44]



ICA factorial representation = ($u_1, u_2, \ldots, u_n$)

Figure 37: The factorial code representation consisted of the independent coefficients, **u**, for the linear combination of basis images in *A* that comprised each face image *x*. [44]

5.1.4 Laplacianfaces and nonlinear dimension reduction

Despite using linear projection to obtain the representation vector of each face image, some researchers claim that the nonlinear projection may yield better representation for face recognition. The Laplacianfaces proposed by He et al. [45] used the locality preserving projections (LPP) [46] to find an embedding that preserves local information, and obtains a face subspace that best detects the essential face mani

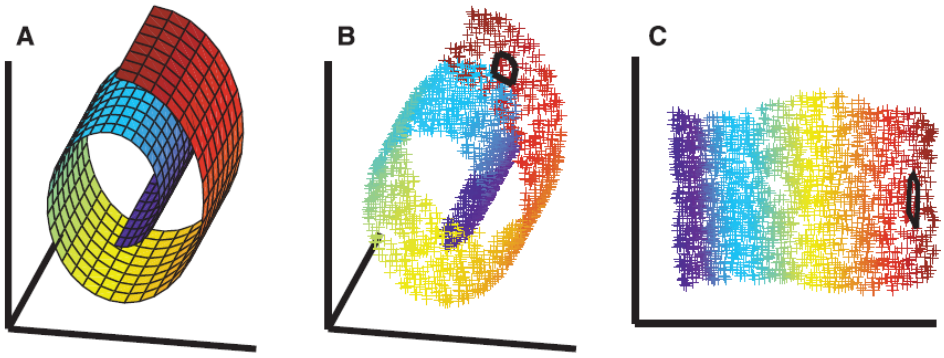


Figure 38: The problem of nonlinear dimension reduction, where a three-dimensional data is generated from a two-dimensional manifold. An unsupervised learning algorithm must discover the global internal coordinates of the manifold without signals that explicitly indicate how the data should be embedded in two dimensions. The color coding illustrates the neighborhood preserving mapping discovered by a nonlinear dimension reduction technique called the LLE (locally linear embedding); black outlines in (B) and (C) show the neighborhood of a single point. Unlike nonlinear dimension reduction techniques, projections of the PCA map faraway data points (in the manifold sense) to nearby points in the plane, failing to identify the underlying structure of the manifold. [47]

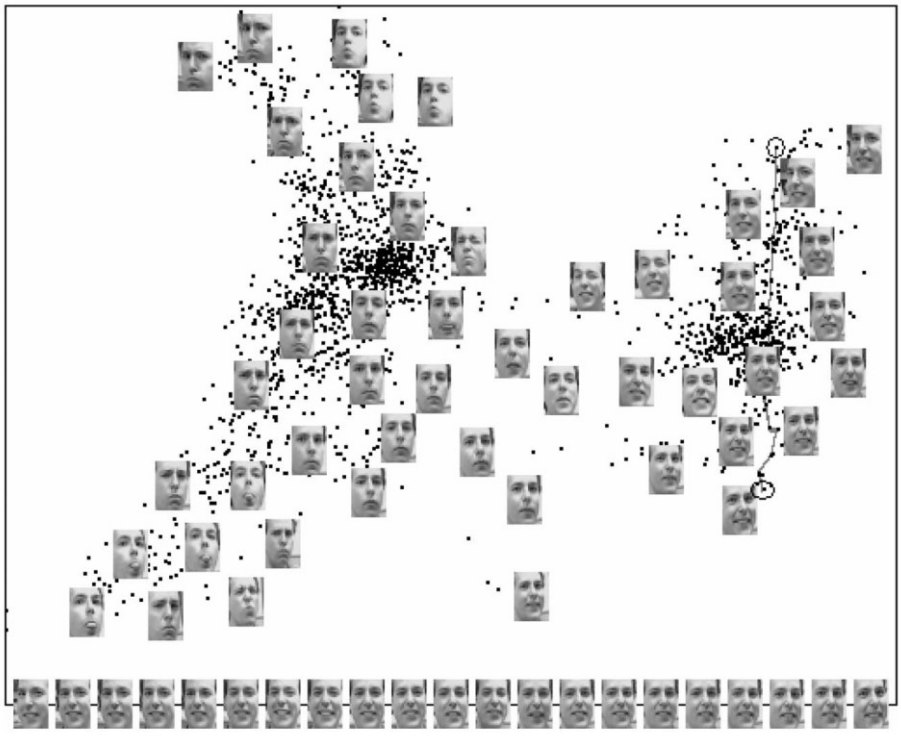


Figure 39: Two-dimensional linear embedding of face images by Laplacianfaces. As can be seen, the face images are divided into two parts, the faces with open mouth and the faces with closed moth. Moreover, it can be clearly seen that pose and expression of human faces change continuously and smoothly, from top to bottom, from left to right. The bottom images correspond to points along the right path (linked by solid line), illustrating one particular mode of variability on pose. [45]

fold structure. The manifold is a low-dimension shape of data distribution embedded in the high-dimension space, as depicted in fig. 38. The linear projection would destroy the low-dimension structure which may make the blue samples closed to the red samples in the dimension-reduced space, while the nonlinear dimension techniques preserve this manifold property. Using the weight vector reached by the LPP, we can train a classifier or use the *K*-NN (K-nearest neighbors) technique for face recognition. Fig. 39 illustrates how the Laplacianfaces preserve the face variation from the high-dimension space into a 2-*D* space, where the closed points definitely have similar appearances.

5.1.5 Robust face recognition via sparse representation

Wright et al. [48] proposed to use the sparse signal representation for face recognition. They used the over-complete database as the projection basis, and applied the L1-minimization algorithm to find the representation vector for a human face. They claimed that if sparsity in the recognition problem is properly harnessed, the choice of features is no longer critical. What is crucial, however, is that whether the number of features is sufficiently large and whether the sparse representation is correctly computed. This framework can handle errors due to occlusion and corruption uniformly by exploiting the fact that these errors are often sparse with respect to the standard (pixel) basis. Fig. 40 shows the overview of their algorithm.

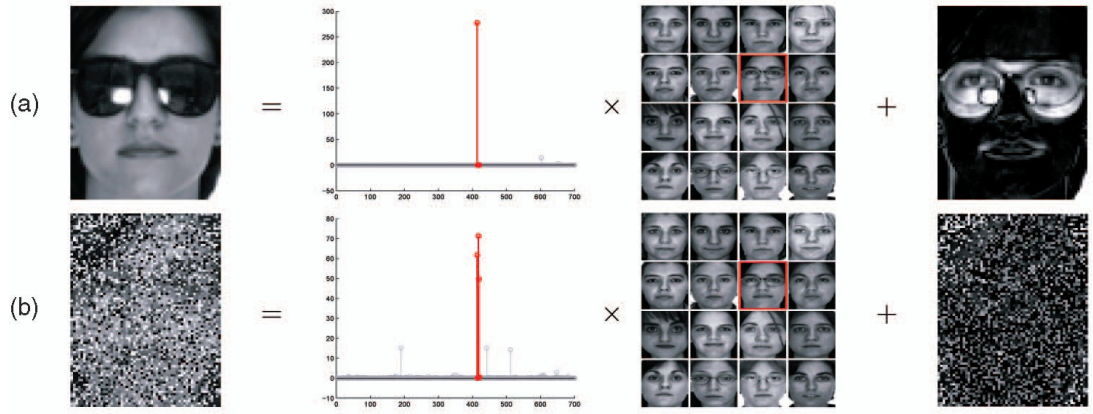


Fig. 40: The sparse representation technique represents a test image (left), which is (a) potentially occluded or corrupted. Red (darker) coefficients correspond to training images of the correct individual. [48]

5.2Feature-based methods

We have briefly compared the differences between holistic-based methods and feature-based methods based on what the information they use from a given face patch, and from another point of view, we can say that holistic-based methods rely more on

statistical learning and analysis, while feature-based methods exploit more ideas from image processing, computer vision, and domain knowledge form human. In this section, we discus two outstanding features for face recognition, the Gabor wavelet feature and the local binary pattern.

5.2.1 Gabor wavelet features with elastic graph matching based methods

The application of Gabor wavelet for face recognition is pioneered by Lades et al.'s work [49]. In their work, the elastic graph matching framework is used for finding feature points, building the face model and performing distance measurement, while the Gabor wavelets are used to extract local features at these feature points, and a set of complex Gabor wavelet coefficients for each point is called a jet. Graph matching based methods normally requires two stages to build the graph g^I for a face image I and compute its similarity with a model graph g^M. During the first stage, g^M is shifted within the input image to find the optimal global offset of g^I while keeping its shape rigid. Then in the second stage, each vertex in g^I is shifted in a topological constraint to compensate the local distortions due to rotations in depth or expression variations. It is actually the deformation of the vertices that makes the graph matching procedure elastic. To achieve these two stages, a cost measure function S(g^M, g^I) is neccesarily to be defined and these two stages terminate when this function reaches the minimum value.

Lades et al.'s [49] used a simple rectangular graph to model faces in the database while each vertex is without the direct object meaning on faces. In the database building stage, the deformation process mentioned above is not included, and the rectangular graph is manually placed on each face and the features are extracted at individual vertices. When a new face I comes in, the distance between it and all the faces in the database are required to compute, which means if there are totally N face models in the database, we have to build N graphs for I based on each face model. This matching process is very computationally expensive especially for large database.Fig.41 shows an example of a model graph and a deformed graph based on it, and the cost function is defined as:

$$S(g^M, g^I) = \sum_n S_m({J_n}^I - {J_n}^M) - \lambda \sum_e (\Delta {\vec{x}_e}^I - \Delta {\vec{x}_e}^M)^2$$

where λ determines the relative importance of jet similarity and the topography term. $\Delta\vec{x}_e$ is the distance vector of the labeled edge e between two vertices, J_n is the set of jets at vertex n, and S_m is the distance measure function between two jets based on the magnitude of jets.

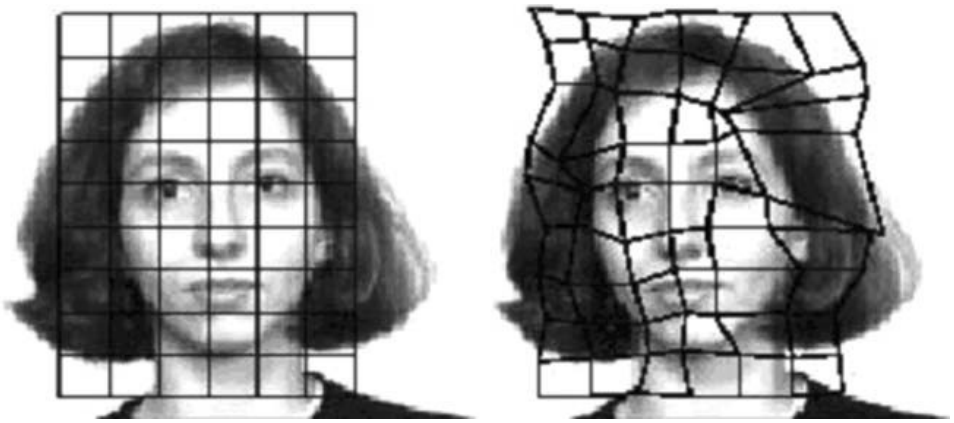
Wiskott et al. [50] proposed an improved elastic graph matching framework to deal with the computational-expensive problem above and enhance the performance.

They employed object-adaptive graph to model faces in the database, which means the vertices of a graph refer to special facial landmarks and enhance the distortion-tolerant ability (see Fig.42). The distance measure function here not only counts on the magnitude information, but also takes in the phase information from the feature jets. And the most important improvement is the used of face bunch graph (FBG), which is composed of several face models to cover a wide range of possible variations in the appearance of faces, such as differently shaped eyes, mouths, or noses, etc. A bunch is a set of jets taken from the same vertex (the same landmark) from different face models and Fig.43 shows the FBG structure. The cost function is redefined as:

$$S(B, g^I) = \frac{1}{N}\sum_n \max_m S_p(J_n{}^I - J_n{}^{B_m}) - \frac{\lambda}{E}\sum_e \frac{(\Delta\vec{x}_e{}^I - \Delta\vec{x}_e{}^B)^2}{(\Delta\vec{x}_e{}^B)^2}$$

where B is the FBG representation, and N and E are the total amounts of vertices and edges in the FBG. B_m denotes the m^{th} model graph of B and S_p is the new-defined distance measure function which takes the phase of jets into account. To build the database, a FBG is first generated and models for individual faces are generated by the elastic graph matching procedure based on FBG. When a new face comes in, the same elastic graph matching procedure based on FBG is executed to generate a new face model, and this model could directly compare with the face models in the database without re-modeling. The FBG serves as the general representation of faces and reduce the computations for face modeling.

Besides these two symbolic examples using the elastic graph matching framework, a number of varied versions have been proposed in literature and readers could found a brief introduction in [51].



(a) (b)

Figure 41: The graphic models of face images. The model graph (a) is built to represent a face stored in the database, and features are directly extracted on vertices in the rectangular graph. When a new face comes in and we want to recognize this person, a deformed graph (b) is generated based on the two- stage process [49].

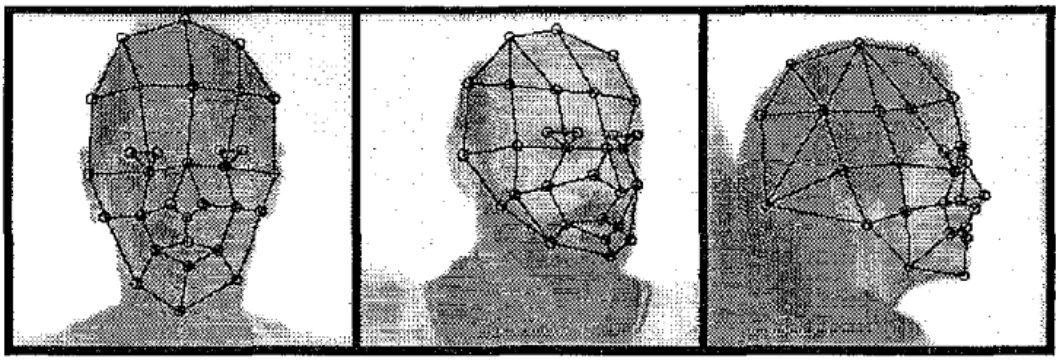


Figure 42: The object-adaptive grids for difference poses. Now the vertices are positioned automatically by elastic bunch graph matching and are located at special facial landscapes. One can see that, in general, the matching finds the fiducial points quite accurately, but still with some miss-positioning [50].

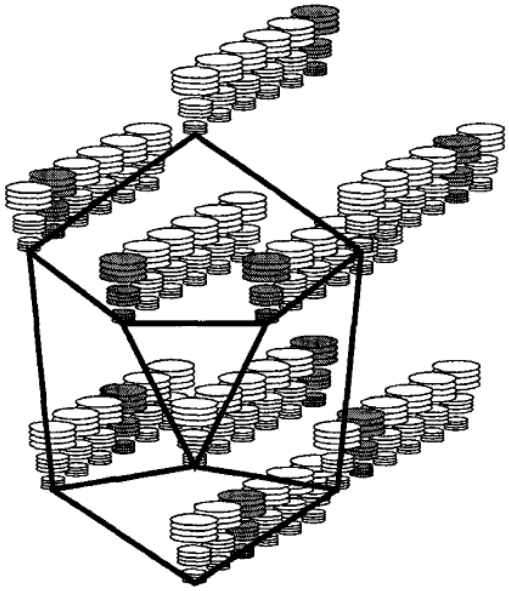


Figure 43: The face bunch graph serves as the general representation of faces. As shown in this figure, there are nine vertices in the graph and each of them contains a bunch of jets to cover the variations in the facial appearance. The edges are represented by the averaged distance vector calculated from all face models sued to build the FBG [50].

5.2.2 Binary features

Besides applying the Gabor wavelet features with elastic graph matching based methods, Ahonen et al. [52] proposed to extract the local binary pattern (LBP) histograms with spatial information as the face feature and use a nearest neighbor classifier based on Chi square metric as the dissimilarity measure. The idea behind using the LBP features is that the face images can be seen as composition of micro-patterns which are invariant with respect to monotonic gray scale transformations. Combining

these micro-patterns, a global description of the face image is obtained.

The original LBP operator, introduced by Ojala et al. [53], is a powerful means of texture description. The operator labels the pixels of an image by thresholding the 3×3-neighborhood of each pixel with the center value and considering the result as a binary number. Then the histogram of the labels can be used as a texture descriptor. Fig. 43 illustrates the basic LBP operator. Later the operator was extended to use neighborhoods of different sizes based on circular neighborhoods and bilinear interpolation of the pixel values [54]. The notation (P,R), where P means the number of sampling points on a circle of radius R, is adopted and illustrated in fig. 44.

Another extension to the original operator uses so called uniform patterns [54]. A local binary pattern is called uniform if it contains at most two bitwise transitions from 0 to 1 or vice versa when the binary string is considered circular. Ojala et al. noticed that in their experiments with texture images, uniform patterns account for a bit less than 90 % of all patterns when using the (8,1) neighborhood and for around 70% in the (16,2) neighborhood.

The following notation for the LBP is used: $\mathrm{LBP}_{P,R}^{u2}$. The subscript represents using the operator in a (P,R) neighborhood. Superscript *u2* stands for using only uniform patterns and labeling all remaining patterns with a single label. A histogram of the labeled image $f_l(x,y)$ can be defined as:

$$H_i = \sum_{x,y} I\{f_{l(x,y)} = i\}, i = 0, ..., n-1$$

, in which n is the number of different labels produced by the LBP operator and

$$I\{A\} = \begin{cases} 1, A \text{ is true} \\ 0, A \text{ is flase.} \end{cases}$$

This histogram contains information about the distribution of the local micro-patterns, such as edges, spots and flat areas, over the whole image. For efficient face representation, one should retain also spatial information. For this purpose, the image is divided into several regions as shown in fig. 45 and the spatially enhanced histogram is defined as:

$$H_{i,j} = \sum_{x,y} I\{f_{l(x,y)} = i\} I\{(x,y) \in R_j\}, i = 0, ..., n-1, j = 0, ..., m-1.$$

In this histogram, we effectively achieve a description of the face on three different level of locality: the labels for the histogram contain information about the patterns on a pixel-level, the labels are summed over a small region to produce information on a region level and regional histograms are concatenated to build a global descrip-

tion of the face.

In the face recognition phase, the nearest neighbor classifier is adopted to compare the distance between the input face and the database. Several metrics could be applied for distance calculation, such as the histogram intersection, log-likelihood statistic, L_1 and L_2 distance, and Chi square statistic (X^2), etc. When the image has been divided into regions, it can be expected that some of the regions contain more useful information than others in terms of distinguishing between people. For example, eyes seem to be an important cue in human face recognition. To take advantage of this, a weight can be set for each region based on the importance of the information it contains. For example, the weighted X^2 statistic becomes

$$X_w^2(S,M) = \sum_{i,j} w_j \frac{(S_{i,j} - M_{i,j})^2}{S_{i,j} + M_{i,j}}$$

, in which w_j is the weight for region *j* and *S* and *M* denote two feature vectors to be compared. Fig. 45 also shows the weights they applied in the experimental results. Later on, several recent works used this feature for face recognition ,such as [55].

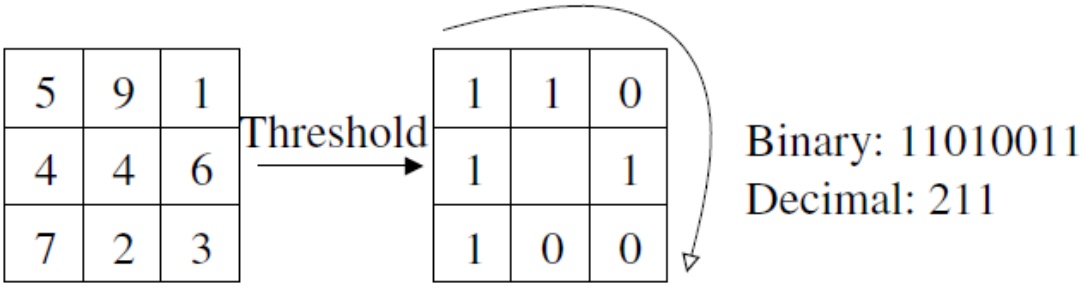


Figure 43: The basic LBP operator. [52]

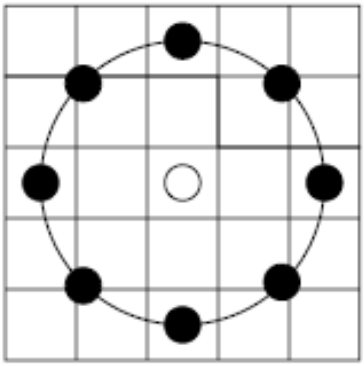
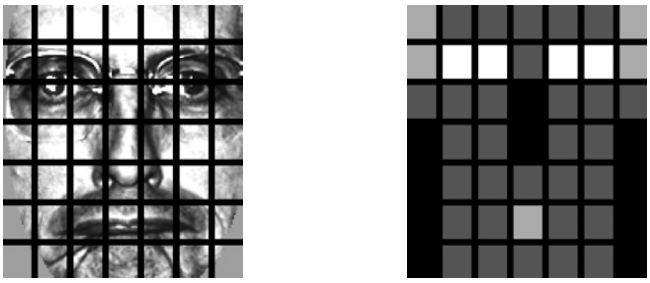


Figure 44: The circular (8,2) neighborhood. The pixel values are bilinearly interpolated whenever the sampling point is not in the center of a pixel. [52]



(a) (b)

Figure 45: (a) An example of a facial image divided into 7×7 windows. (b) The weights set for weighted X^2 dissimilarity measure. Black square indicate weight 0.0, dark gray 1.0, light gray 2.0 and white 4.0. [52]

5.3Template-based methods

The recognition system based on the two methods introduced above usually perform feature extraction for all face images stored in the database and train classifiers or define some metric to compute the similarity of a test face patch with each class person class. To overcome variations of faces, these methods increase their database to accommodate much more samples and expect the trained transformation basis or defined distance metric could attenuate the intra-class variation while maintaining the inter-class variation. Traditional template-matching is pretty much like using distance metric for face recognition, which means selecting a set of symbolic templates for each class (person), the similarity measurement is computed between a test image and each class, and the class with the highest similarity score is the selected as the correct match. Recently, deformable template techniques are proposed [31]. In contrast to implicitly modeling intra-class variations (ex. increasing database), deformable template methods explicitly models possible variations of human faces from training data and are expected to deal with much severe variations. In this section, we introduce the face recognition technique based on the ASM and the AAM described in Section 4.3.1.

From the introduction in section 4.3.1, we know that during the face detection process, the AAM will generates a parameter vector *c* which could synthesize a face appearance that is best fitted to the face shown in the image. Then if we have a well-chosen database which contains several significant views, pose, expressions of each person, we can achieve a set of AAM parameter vectors to represent each identity. To compare the input face with the database, Edwards et al. [56] proposed to use the Mahalonobis distance measure for each class and generate a class-dependent metric to encounter the intra-class variation. To better exploit the inter-class variation against the intra-class variation, they also used the linear discriminant analysis (LDA) for dimension reduction and classification task.

5.4Part-based methods

Following the ideas presented in Section 4.5, there have been several researches these years exploiting information from facial characteristic parts or parts that are robust against pose or illumination variation for face recognition. To be distinguished from the feature-based category, the part-based methods detect significant parts from the face image and combine the part appearances with machine learning tools for recognition, while the feature-based methods extract features from facial feature points or the whole face and compare these features to achieve the recognition purpose. In this subsection, we introduced two techniques, one is an extension system of the method described in Section 4.5.2, and one is based on the SIFT (scale-invariant feature transform) features extracted from the face image.

5.4.1 Component-based face recognition

Based on the face detection algorithm described in Section 4.5.2, Heisele et al. [57] compared the performance of the component-based face recognition against the global approaches. In their work, they generated three different face recognition structures based on the SVM classifier: a component-based algorithm based on the output of the component-based face detection algorithm, a global algorithm directly fed by the detected face appearance, and finally a global approach which takes the view variation into account.

Given the detected face patches, the two global approaches have the only difference that whether the view variation of the detected face is considered. The algorithm without this consideration directly builds a SVM classifier for a person based on all possible views, while the one with this consideration first divides the training images of a person into several view-specific clusters, and then trains one SVM cluster for each of them. The SVM classifier is originally developed for binary classification case, and to extend for multi-class tasks, the one-versus-all and the pair-wise approaches are described in [58]. The view-specific clustering procedure is depicted in fig. 46.

The component-based SVM classifier is cascaded behind the component-based face detection algorithm. After a face is detected in the image, they choose 10 of the 14 detected parts, normalized them in size and combined their gray values into a single feature vector. Then a one-versus-all multi-class structure with a linear SVM for each person is trained for face recognition purpose. In fig. 47, we show the face detection procedure, and in fig. 48, we present the detected face and the corresponding 10 components fed into the face recognition algorithm.

In the experimental results, the component system outperforms the global systems for recognition rate larger than 60% because the information fed into the clas-

sifiers capture more specific facial features. In addition, the clustering leads to a significant improvement of the global method. This is because clustering generates view-specific clusters that have smaller intra-class variations than the whole set of images of a person. Based on these results, they claimed that a combination of weak classifiers trained on a properly chosen subsets of the data can outperform a single, more powerful classifier trained on the whole data.

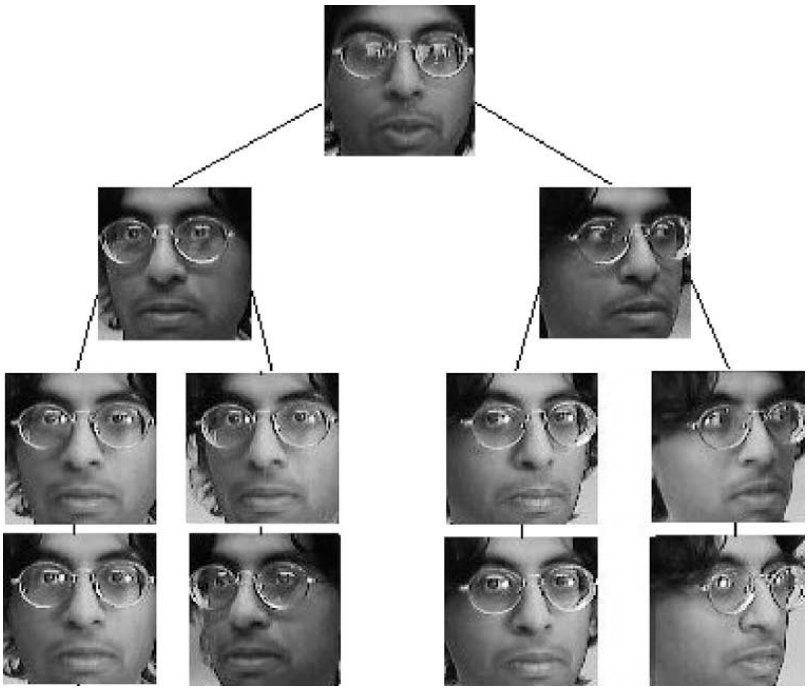


Figure 46: Binary three of face images generated by divisive clustering. [57]

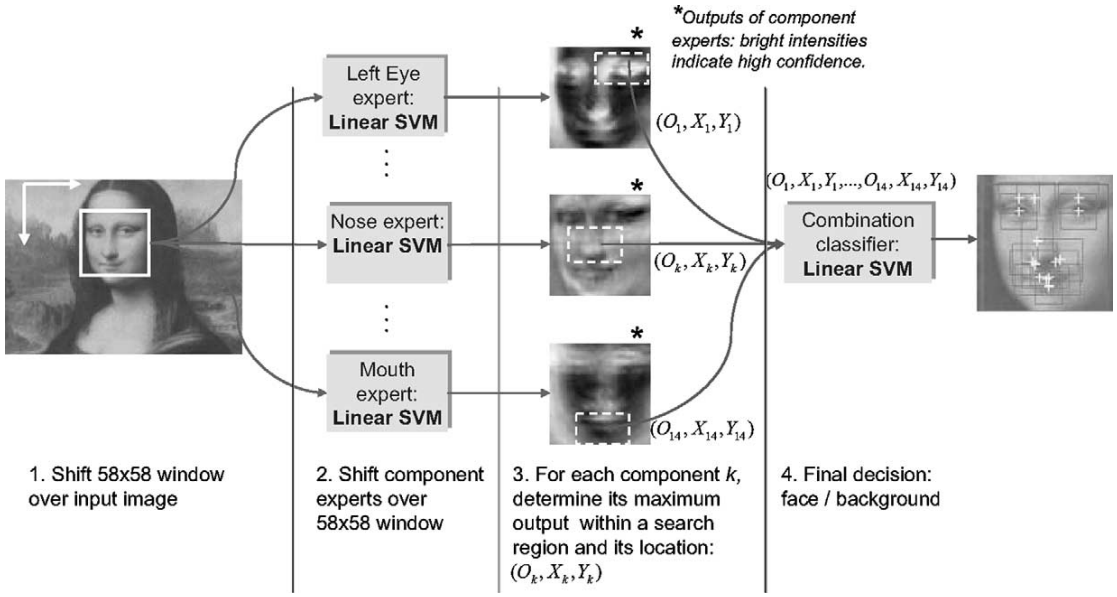


Figure 47: System overview again of the component-based face detector using four components. [57]

Figure 48: Examples of the component-based face detection and the 10 components used for face recognition. [57]

5.4.2 Person-specific SIFT features for face recognition

The scale-invariant feature transform (SIFT) proposed by Lowe et.al [34] has been widely and successfully applied to object detection and recognition. In the works of Luo et al. [59], they proposed to use the person-specific SIFT features and a simple non-statistical matching strategy combined with local and global similarity on key-point clusters to solve face recognition problems.

The SIFT is composed of two functions, the interest-point detector and the region-descriptor. Lowe et al. used the difference-of-Gaussian (DOG) algorithm to detect these points in a scale-invariant fashion, and generated the descriptor based on the orientation and gradient information calculated in a scale-specific region around each detected point. Fig. 49 shows the SIFT features extracted on sample faces and some corresponding matching point in two face images. In each face image the number and the positions of the features selected by the SIFT point detector are different, so these features are person-specific. In order to only compare the feature pairs with similar physical meaning between faces in the database and the input face, same number of sub-regions are constructed in each face image to compute the similarity between each pair of sub-regions based on the features inside and at last get the average similarity values. They proposed to ensemble a *K*-means clustering scheme to construct the sub-regions automatically based on the locations of features

in training samples.

After constructing the sub-regions on face images, when testing a new image, all the SIFT features extracted from the image are assigned into corresponding sub-regions based on the locations. The construction of five sub-regions is illustrated in fig. 50, and it can be seen that the centers of regions denoted by crosses just correspond to two eyes, nose and two mouth corners that agree with the opinion of face recognition experience as these areas are the most discriminative parts of face images. Based on the constructed sub-regions, a local-and-global combined matching strategy is used for face recognition. The details of this matching scheme are referred in [59].

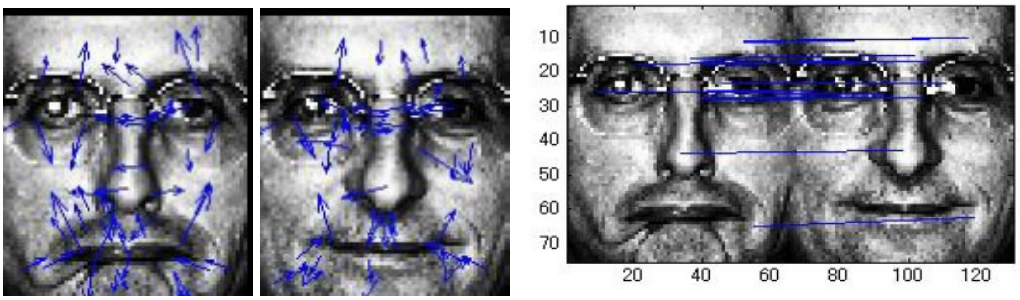


Figure 49: SIFT features on sample images and features matches in faces with expression variation. [59]

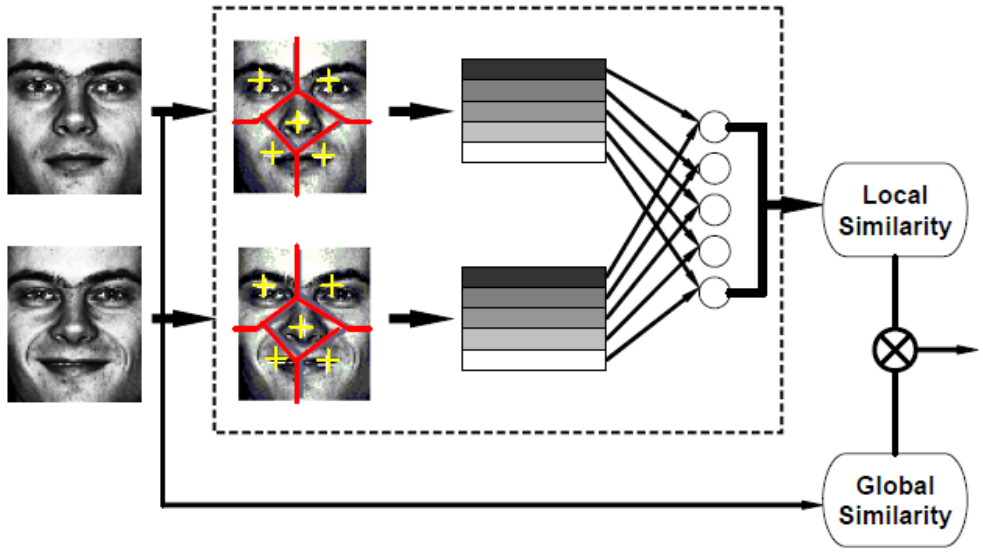


Figure 50: Sub-region construction and similarity computation scheme for the face recognition system. [59]

6. Comparison and Conclusion

In this section, we'll give summaries on face detection and face recognition techniques during the past twenty year as well as popular face data set for experiments and their characteristics.

Table 7: The summary of face detection techniques

Method	Category	Characteristics
Hierarchical knowledge-based [8]	Knowledge-based	Coarse-to-fine procedure
Horizontal / vertical projection [9]	Knowledge-based	
Face Detection Using Color Information [10]	Feature-based	Combining skin-color detection, face shape verification, and facial feature configuration for detection
Face detection based on random labeled graph matching [11]	Feature-based	Combining simple features with statistical learning and estimation
Active appearance model [19]	Template matching	Learning facial shape and appearance variation by data
Example-based learning [21]	Appearance-based	Learning the face and non-face distribution by mixture of Gaussian
Haar features with Adaboost [22]	Appearance-based	Adaboost for speed-up
Generative models [36]	Part-based	Unsupervisedly extracting important facial features, and learning the relation among parts and discrimination between face and non-face by the graphical model structure.
Component-based with SVM [37]	Part-based	Learning global and local SVM for detection

Table 8: The summary of face recognition techniques

Method	Category	Characteristics
PCA [39]	Holistic-based	PCA for learning eigenfaces, unsupervised
LDA [40]	Holistic-based	LDA for learning fisherfaces, supervised
2D-PCA [41]	Holistic-based	2D-PCA for better statistical properties
ICA [44]	Holistic-based	ICA for catch facial independent components, two architectures are proposed
Laplacianfaces [45]	Holistic-based	Nonlinear dimension reduction for finding bases, LPP
Evolutionary pursuit [43]	Holistic-based	Using the genetic algorithm for finding the best projection bases based on generalization error
Kernel PCA And Kernel LDA [42]	Holistic-based	Mapping the image into higher-dimensional space by the kernel function, and exploit the PCA and LDA bases there
Sparse representation [48]	Holistic-based	Using L1 minimization and over-complete dictionary for finding sparse representation
Gabor and dynamic link architecture [49]	Feature-based	Gabor features extracted at facial feature locations, while performing one-by-one matching
Gabor and elastic bunch graph matching [50]	Feature-based	Gabor features extracted at facial feature locations, and obtaining the robust representation by the FBG matching.
LBP [52]	Feature-based	Local binary patterns are introduced
LTP [55]	Feature-based	Binary into ternary
AAM [56]	Template matching	AAM parameters for classification learning

Component-base [57]	Part-based	Comparing global and component representation, while a SVM classifier for each person is not suitable in practice.
SIFT [59]	Part-based	Using SIFT feature with spatial constraints to compare faces

Table 9: The summary of popular databases used for detection and recognition tasks (from [3])

Name	RGB/gray	Image size	# people	Pictures/person	Conditions	Available
AR Face Database*	RGB	576x768	126	26	i, e, o, t	Yes
Richard's MIT	RGB	480x640	154	6	p, o	Yes
CVL	RGB	640x480	114	7	p, e	Yes
The Yale Face Database B*	Gray	640x480	10	576	p, i	Yes
The Yale Face Database*	Gray	320x243	15	11	i, e	Yes
PIE*	RGB	640x486	68	~608	p ,i, e	Yes
The UMIST Face Database	Gray	220x220	20	19-36	p	Yes
Olivetti Att-ORL*	Gray	92x112	40	10		Yes
JAFFE	Gray	256x256	10	7	e	Yes
The Human Scan	Gray	384x286	23	~66		Yes
XM2VTSDB	RGB	576x720	295		p	With pay
FERET*	RGB/gray	256x384	30000		p, i, e, i/o, t	Yes

The (*) points out most used databases. Image variations are indicated by (i) illumination, (p) pose, (e) expression, (o) occlusion, (i/o) indoor/outdoor conditions and (t) time delay.

Finally, there is still no robust face detection and recognition technique for unconstraint real-world applications, and these are our direction for future works.

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