1 Person-Specific Characteristic Feature Selection for Face Recognition

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1.1 INTRODUCTION

Fingerprint recognition and/or iris recognition have proven to be very robust when the cooperation of the human subject can be assumed, both during enrollment and during test. This makes them ideal for limiting entry into secured areas (such as buildings) to known and trusted individuals. However, these biometrics are not very useful for recognizing people in public places, where there is little or no motivation to cooperate with the system.

In contrast, face recognition has the potential for recognizing people at a distance, without their knowledge or cooperation. For decades, banking, retail, commercial, and industrial buildings have been populated with surveillance cameras that capture video streams of all people passing through critical areas. More recently, as a result of threats to public safety, some public places (such as in Glasgow and London) have been heavily populated with video surveillance cameras. On average, a person moving through London is captured on video over 5 times a day. This offers an unprecedented basis for developing and testing face recognition as a biometric for security and surveillance.

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Given this great potential, it is not surprising that many private corporations have attempted to develop and deploy face recognition systems, as an adjunct to existing video security and surveillance systems. However, the performance of these systems has been disappointing. Depending on how such a system is adjusted, miscreants might easily pass through the system undetected, or innocent people might be incessantly inconvenienced by false alarms.

One of the most difficult problems that face recognition researchers encounter in surveillance applications is that face databases of miscreants typically contain only frontal and profile views of each person's face, with no intermediate views. Surveillance videos captured of the same person with the same camera in the same lighting conditions might have face images that look quite different, due to pose angle variations, making it very difficult to compare captured face images to those in a database. Combine this problem with the fact that miscreants are highly motivated to disguise their identity, and the fact that face databases often contains thousands of faces, and the problem seems insurmountable.

Given all of these complicating factors, it is premature to rely upon face recognition systems for detecting miscreants in public places. On the other hand, the use of face recognition in controlled access applications (where users are highly motivated to cooperate, and where face database images can be both captured and tested with the same camera under the same illumination conditions) is certainly within the limitations of current face recognition algorithms.

1.1.1 Employing face recognition to facilitate social interactions

However, there is a real-world application for face recognition that is moderately challenging, but still potentially within the realm of possibility. When people who are blind enter a room, they might find it awkward to initiate social interactions because they don't know how many people are in the room, who those people are, or where they are standing [1] [2]. A robust, wearable face recognition device could solve this problem.

This problem is simplified considerably by the fact that, on a day-to-day basis most people encounter a limited number of people whom they need to recognize. It is further simplified by the fact that people typically don't attempt to disguise their appearance in social situations. When a new person is encountered, the system could employ face detection to extract and save a sequence of face images captured during a conversation. This would provide a wide variety of facial expressions and pose angles, that could be stored in a database, and used for training a face recognition algorithm.

As people use such an assistive device over an extended period of time, they will learn both its abilities and its limitations. Conjectural information from the system can then be combined with the user's other sensory abilities (especially hearing) to jointly ascertain the identity of the person. This synergy between the user and the system relaxes some of the stringent requirements normally placed on face recognition systems.

However, such an assistive technology application still poses some significant challenges for researchers. One problem is the extreme variety of in lighting conditions encountered during normal daily activities. While there are standards for indoor office lighting that tend to provide diffuse and adequate lighting, lighting in other public places might vary considerably. For example, large windows can significantly alter lighting conditions, and incandescent lighting is much more yellow than florescent lighting. Outdoor lighting can be quite harsh in full sunlight, and much more blue and diffuse in shadows. A person who is blind might not be aware of extreme lighting conditions, so the system would need to either (1) be tolerant of extreme variations or (2) recruit the user to ameliorate those extreme conditions.

In summary, the development of an assistive face recognition system for people who are blind provides a more tractable problem for face recognition

[1] In order to understand the assistive technology requirements of people who are blind, we conducted two focus group studies (one in Tempe, Arizona USA - 9 participants, and another in Tucson, Arizona USA - 11 participants) which included:

1. students and adult professionals who are blind,
2. parents of individuals who are blind
3. professionals who work in the area of blindness and visual impairments

There was unanimous agreement among participants that a technology that would help people with visual impairment to recognize people or hear them described would significantly enhance their social life.

[2] To quote some candidates opinion about face recognition technology in a social setting:

- "It would be nice to walk into a room and immediately get to know who are all in front of me before they start a conversation".
- One young man said, "It would be great to walk into a bar and identify beautiful women".

researchers than security and surveillance applications. It imposes a somewhat less stringent set of requirements because (1) the number of people to be recognized is generally smaller, (2) facial disguise is not a serious concern, (3) multiple pose angles and facial expressions of a person can be captured as training images, and (4) the person recognition process can be a collaborative process between the system and the user.

In an attempt to provide such an assistive face recognition system, we have developed a new methodology for face recognition that detects and extracts unique features on a person's face, and then uses those features to recognize that person. Contrast this with conventional face recognition algorithms that might avoid the use of a few distinguishing features because that approach might make the system very vulnerable to disguise.

1.2 FACE RECOGNITION IN HUMANS

For decades, scientists in various research areas have studied how humans recognize faces. Developmental psychologists have studied how human infants start to recognize faces, cognitive psychologists have studied how adolescents and adults perform face recognition; neuroscientists have studied the visual pathways and cortical regions used for recognizing faces, and neuropsychologists have attempted to integrate knowledge from neurobiological studies with face recognition research. Computer vision researchers are relatively new to this area, and have attempted to develop face recognition algorithms using image processing methods. Only recently have computer vision researchers been motivated to better understand the process by which humans recognize faces, in order to use that knowledge to develop robust computational models. Their new interest has lead to more inter-disciplinary face recognition research, which will likely aid our understanding of face recognition.

New studies have shown that humans, to a large extent, rely on both the featural and configural information in face images to recognize faces [20]. Featural information provides details about the various facial features, such as the shape and size of the nose, the eyes, and the chin. Configural information defines the locations of the facial features, with respect to each other. Psychologists Vicki Bruce and Andrew Young [4] agree with this dual representation, saying that humans create a view-centric description of a human face by relying upon feature-by-feature perceptual input, which is then combined into a structural model of the face.

Sadar et al [19] showed that characteristic facial features are important for recognizing famous faces. For example, when they erased eye-brows from famous people's faces, face recognition by human participants was adversely affected. Young [38] showed that human participants were confused when asked to recognize faces that combined facial features from different famous faces. These studies suggest that the details of facial features are important in the recognition of faces.

However, [21] showed that the relative locations of the facial features was also very important for the recognition of faces. They collected face images of famous personalities, and then changed the aspect ratio of those images, such that the height was greatly compressed, while the width was emphasized. Surprisingly, all the resulting face images were still recognizable, despite their contorted appearance, as long as the relative locations of the features were maintained within the distorted image. This study suggests that humans can flexibly use the configural information when recognizing faces.

Another important area of research in the human perception of faces has been in understanding the medical condition of face blindness, called *prosopagnosia*. People with prosopagnosia are unable to recognize faces including their own. Until recently it was assumed that prosopagnosia was acquired often as a result of a localized stroke. However new evidence suggests that a substantial portion of the general population have a congenital form of prosopagnosia [17]. Kennerknecht et al [9] conducted a survey of 789 students in 2006 which showed that 17 (2.5%) suffered from congenital prosopagnosia. These students went about their daily life without realizing their disorder in face recognition.

Other studies at the Perception research centers at Harvard and Univ College of London have shown that prosopagnosics recognize people using unique personal characteristics, such as hair style, gait, clothing, and voice. These findings suggest that the detection of unique personal characteristics might provide a basis for face recognition systems to better recognize people. Since current methods of face recognition have met with only limited success, it makes sense to explore the use of this alternative approach.

Research in Own-Race Bias (ORB) in face recognition [26] has also revealed some interesting results regarding human face recognition capabilities. David Turk et al. found that, when humans are presented with new objects or new faces, they initially learn to recognize those objects and faces based on their distinctive features. Then, as familiarity increases, they incorporate configural information, moving towards holistic recognition. This study suggests that distinctive features are important during the initial stages of face recognition, and that configural information subsequently provides additional useful information.

Distinctive facial features can take many different forms. For example, after a first encounter with a person who has a handlebar moustache, we readily recognize that person by the presence of his distinctive feature. Similarly, a person with a large black mole on her face will be remembered by first-time acquaintances by that feature. Given the current limited understanding of how humans recognize faces, it makes sense to use these observations as the basis for a new approach to face recognition.

The research described in this chapter is based on the approach of identifying distinctive facial features that can be used to distinguish each person's face from other faces in a face database. In recognition of the role played by configural information in the later stages of face recognition, it also takes into account the location of these features with respect to each other. The results of our research suggest that this approach can be very effective for distinguishing one person's face from other faces.

1.3 OUR APPROACH TO FACE RECOGNITION

Having introduced the potential for using characteristic person-specific features for face recognition, we now turn our attention towards the development of a method for discovering such features, and for using them to index face images. Then we propose a novel methodology for face recognition, using person-specific feature extraction and representation. For each person in a face database, a learning algorithm discovers a set of distinguishing features (each feature consisting of a unique local image characteristic, and a corresponding face location) that are unique to that person. This set of characteristic facial features can then be compared to the normalized face image of any person, to determine the presence or absence of those features. Because a unique set of features is used to identify each person in the database, this method effectively employs a different feature space for each person, unlike other face recognition algorithms that assign all of the face images in the database to a locality in a shared feature space. Face recognition is then accomplished by a sequence of steps, in which query face images is mapped into a locality within the feature space of each person in the database, and its position is compared to the cluster of points in that space that represents that person. The feature space in which the query face images are closest to the cluster is used to identify the query face images.

Having introduced the conceptual theory behind a person-specific characteristic feature extraction approach to face recognition, we now propose in the subsequent sections a method for detecting and extracting such features from face images, and for constructing a feature space that is unique to each person in the database.

1.4 FEATURE EXTRACTORS

1.4.1 What is a Feature?

The task of face recognition is inherently a multi-class classification problem. For every face image X, there is an associated label y that is the name of the class, i.e. the name of the person depicted in the image. While X represents the image of the person, there is no inherent constraint on whether the image is a color RGB, HUV or YCbCr image, or a gray-scale image with a gray-scale range of 0 to 255, or even spectral representation that is extracted from the face image using Fourier transform or Wavelets. Irrespective of the image representation, the basis vectors spanning that representation are called features. The feature space spanned by these basis vectors is partitioned by the decision boundaries that ultimately define the different classes in the multi-class problem of face recognition. In this work, we choose a particular set Gabor filters as feature detectors, and each of those feature detectors for each person in the database, and that set of Gabor filters spans a unique feature space for that person.

1.4.2 Gabor Features

Gabor filters are a family of functions (sometimes called Gabor Wavelets) that are derived from a mother kernel (a Gabor Function) by varying the parameters of the kernel. As with any wavelet filters, the Gabor filters extract local spatial frequency content from the underlying image. Gabor Filters specifically capture the spatial location and spatial orientation of the intensity variations in the image underneath the filter's location. By varying the spatial frequency and the spatial scope of the filters, it is possible to extract a Gabor coefficient that partially describes the nature of the image underneath it. The coefficients obtained by filtering a locality in a face image with a set of different Gabor Filters are called Gabor Features.

1.4.2.1 Use of Gabor Filters in Face Recognition Gabor filters have been widely used to represent the receptive field sensitivity of simple cell feature detectors in the human primary visual cortex. Recognizing this fact, Gabor features have been widely used by face recognition researchers. Over the last few years, the extensive use of Gabor wavelets as generators of feature spaces for face recognition, has led to objective studies of the strength of Gabor features for this application. For example, Shan et al [Shan2004] reviewed the strength of Gabor features for face recognition using an evaluation method that combined both alignment precision and recognition accuracy. Their experiments confirmed that Gabor features are robust to image variations caused by the imprecision of facial feature localization. As indicated by Gökberk et al [5], several studies have concentrated on examining the importance of the Gabor kernel parameters for face analysis. These include: the weighting of Gabor kernel-based features using the simplex algorithm for face recognition [31], the extraction of facial subgraphs for head pose estimation [11], the analysis of Gabor kernels using univariate statistical techniques for discriminative region finding [7], the weighting of elastic graph nodes using quadratic optimization for authentication [25], the use of principal component analysis (PCA) to determine the importance of Gabor features [13], boosting Gabor features [37] and Gabor frequency/orientation selection using genetic algorithms [30].

A relevant work on Gabor Filters for face recognition that is closely related to the research presented here is by Wiskott and von der Malsburg [33]. Their work [29] [2] [32] [34], [33] proposes a framework for face recognition that is based on modeling human face images as labeled graph. Termed *Elastic Bunch Graph Matching* (EBGM), the technique has become a cornerstone in face recognition research. Each node of the graph is represented by a group of Gabor filters/wavelets (called ”jets”) which are used to model the intensity variations around their locations. The edges of the graph are used to model the relative location of the various jets. Since the jets represent the underlying image characteristics, it is desirable to place them on fiducial points on the face. This is achieved by *manually* marking the locations of the facial fiducial points using a small set of controlled graphs that represent “general face knowledge”, which represents an average geometry for the human face. In our work, a genetic algorithm is used to obtain the spatial location of the fiducial points. Besides automating the process of locating these points, our work identifies spatial locations on the face image that are unique to every single person, rather than relying on an average geometry.

Closely following the work of Wiskott et. al., Lyons et. al. [16] proposed a technique that uses Gabor Filter coefficients extracted at 1) automatically located rectangular grid points or 2) manually selected image feature points. These coefficients are then used to bin face images based on sex, race and expression. The technique relies on a combined Principal Component Analysis (PCA) dimensionality reduction and Linear Discriminant Analysis (LDA) classification over the extracted Gabor coefficients, to achieve a pooling of images. While the classification task is not related directly to *identifying* individuals from face images, this technique also demonstrates the ability of Gabor Filters to extract features that can encode subtle variations on facial images, providing a basis for face identification.

1.4.2.2 Gabor Filters Mathematically, Gabor Filters can be defined as follows:

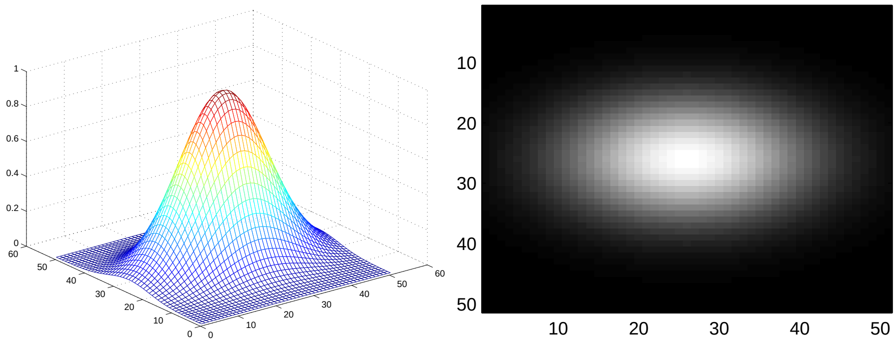
$$\Psi_{\omega,\theta}(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} \cdot G_\theta(x,y) \cdot S_{\omega,\theta}(x,y) \tag{1.1}$$

$$G_\theta(x,y) = \exp\left\{-\left(\frac{(x\cos\theta + y\sin\theta)^2}{2\sigma_x^2} + \frac{(-x\sin\theta + y\cos\theta)^2}{2\sigma_y^2}\right)\right\} \tag{1.2}$$

$$S_{\omega,\theta}(x,y) = \left[\exp\left\{i\left(\omega x\cos\theta + \omega y\sin\theta\right)\right\} - \exp\left\{-\frac{\omega^2\sigma^2}{2}\right\}\right] \tag{1.3}$$

where,

- $G_\theta(x,y)$ represents a Gaussian Function.
- $S_{\omega,\theta}(x,y)$ represents a Sinusoid Function.
- (x,y) is the spatial location where the filter is centered with respect to the image axis.
- ω is the frequency parameter of a 2D Sinusoid.



(a) (b)

Fig. 1.1 (a) 3D representation of a Gaussian mask; $\sigma_x = 10$, $\sigma_y = 15$ and $\theta = 0$ (b)Image of the Gaussian mask $\sigma_x = 10$, $\sigma_y = 15$ and $\theta = 0$

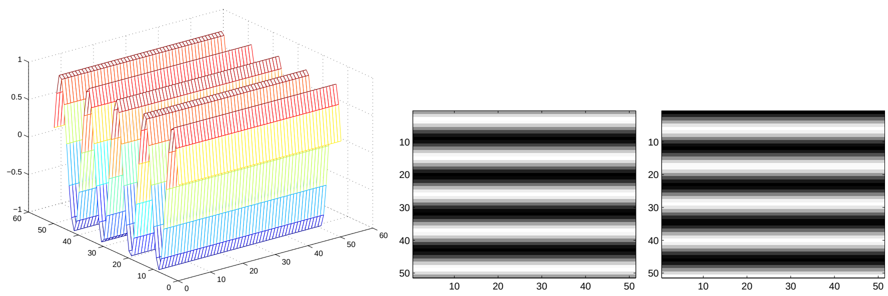
- σ_{dir}^2 represents the variance of the Gaussian (and thus the filter) along the specified direction. *dir* can either be x or y. The variance controls the region around the center where the filter has influence.

From the definition of Gabor filters, as given in Equation 1.1, it is seen that the filters are generated by multiplying two components: a Gaussian Function $G_\theta(x, y)$ (Equation 1.2) and a Sinusoid $S_{\omega,\theta}(x, y)$ (Equation 1.3). The following discussions detail the two components of Equation 1.1.

1.4.2.3 Gaussian Function The 2D Gaussian function defines the spatial spread of the Gabor filter. This spread is defined by the variance parameters of the Gaussian, along the x and y direction together with the orientation parameter θ. Figure 1.1(a) shows a 3D representation of the Gaussian mask generated with $\sigma_x = 10$ and $\sigma_y = 15$ and rotation angle $\theta = 0$. The image in Figure 1.1(b) shows the region of spatial influence of an elliptical mask on an image, where the variance in the x direction is larger than the variance in the y direction.

Typically the Gaussian filter has the same variance along both the x and y directions, that is $\sigma_x = \sigma_y = \sigma$. Under such conditions the rotation parameter θ does not play any role as the spread will be circular.

1.4.2.4 Sinusoid The 2D complex Sinusoid defined by Equation 1.3 generates the two Sinusoidal components of the Gabor filters which (when applied to an image) extracts the local frequency content of the intensity variations in the signal. The complex Sinusoid has two components (the real and the imaginary parts) which are two 2D sinusoids that are phase shifted by $\frac{\pi}{2}$ radians. Figure 1.2(a) shows the 3D representation of a Sinusoidal signal (either real or imaginary) at $\omega = 0.554$ radians and $\theta = 0$ radians, while Figure 1.2(b)



(a) (b) (c)

Fig. 1.2 (a)3D representation of a Sinusoid $S_{\omega,\theta}$
(b)Image representation of the real part of the complex Sinusoid $\Re\{S_{\omega,\theta}\}$
(c)Image representation of the imaginary part of complex Sinusoid $\Im\{S_{\omega,\theta}\}$

and 1.2(c) show an image of the real and imaginary parts of the same complex Sinusoid, respectively. It can be seen that the two filters are similar, except for the π radian phase shift.

Multiplying the Gaussian and the sinusoid generates the complex Gabor filter, as defined in Equation 1.1. If $\sigma_x = \sigma_y = \sigma$, then the real and imaginary parts of this complex filter can be described as follows.

$$\Re\{\Psi_{\omega,\theta}(x,y)\} = \frac{1}{2\pi\sigma^2} \cdot G_\theta(x,y) \cdot \Re\{S_{\omega,\theta}(x,y)\} \tag{1.4}$$

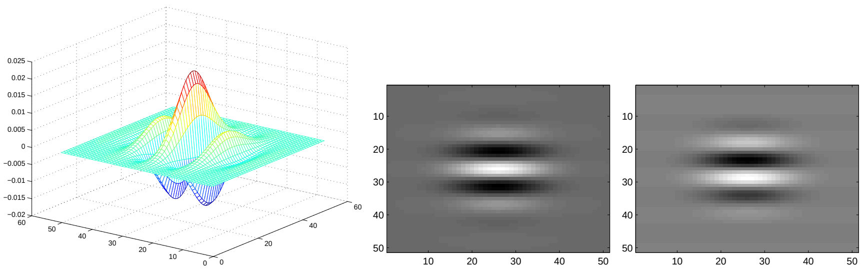
$$\Im\{\Psi_{\omega,\theta}(x,y)\} = \frac{1}{2\pi\sigma^2} \cdot G_\theta(x,y) \cdot \Im\{S_{\omega,\theta}(x,y)\} \tag{1.5}$$

Figure 1.3(a) shows the 3D representation of a Gabor filter (either real or imaginary) at $\omega = 0.554$ radians, $\theta = 0$ radians, and $\sigma = 10$ and Figure 1.3(b) and 1.3(c) show an image with the real and imaginary parts of the complex filter.

In order to extract a Gabor feature at a location (x, y) of an image I, the real and imaginary parts of the filter are applied separately to the same location in the image, and a magnitude is computed from the two results. Thus, the Gabor filter coefficient at a location (x, y) in an image I with a Gabor filter $\Psi_{\omega,\theta}$ is given by

$$C_\Psi(x,y) = \sqrt{\left(I(x,y) * \Re\{\Psi_{\omega,\theta}(x,y)\}\right)^2 + \left(I(x,y) * \Im\{\Psi_{\omega,\theta}(x,y)\}\right)^2} \tag{1.6}$$

In our experiments, a *Gabor filter bank* was created by varying three parameters of $\Psi_{\omega,\theta}$: (1) the frequency parameter ω, (2) the orientation parameter θ, and (3) the variance parameter σ. We chose five values for each of these parameters thereby generating 125 different Gabor filters.



(a) (b) (c)

Fig. 1.3 (a)3D representation of a Gabor filter $\Psi_{\omega,\theta}$
(b)Image representation of the real part of Gabor filter $\Re\left\{\Psi_{\omega,\theta}\right\}$
(c)Image representation of the imaginary part of Gabor filter $\Im\left\{\Psi_{\omega,\theta}\right\}$

- $\omega = \left(2^{(-f+2)/2} \cdot \pi\right)$ where, $f = \{0, 1, 2, 3, 4\}$
- $\theta = \left(\frac{\pi}{2} \cdot \frac{1}{5} \cdot t\right)$ where, $t = \{0, 1.25, 2.5, 3.75, 5\}$
- $\sigma = \{5, 10, 15, 20, 25\}$

1.5 THE LEARNING ALGORITHM

The proposed method uses the above described Gabor filters to find distinguishing features (and corresponding feature locations) within a face image. That is, for each person in the database, the algorithm finds a set of Gabor filters which, when applied at their corresponding (x, y) locations within the image will produce coefficients that are unique for that individual. This means that all of the 125 Gabor filters in the filter bank are applied at each and every location of each of the individual's face images, and then tested for their ability to distinguish every individual. Given a 128×128 face image, there will be $128 \times 128 \times 125 \times n$ filter coefficients that will be generated per face image per person, where n is the number of characteristic features to be extracted for each person. This must be computed for every person in the training set, which further increases the search space. To search such a vast space of parameter values (the size of the Gaussian mask, the frequency of the complex sinusoid, the orientation of the entire Gabor filter, and the (x, y) location where the filter is placed) it is important that some scheme for effective search be incorporated into the system. To this end, we have chosen Genetic Algorithms to conduct the search. For each person in the training set, all of the face images that depict to that person are indexed as positives, while all of the other face images in the database are indexed as negatives. Dedicated Genetic Algorithm based search is conducted with these positive and negative images, with the aim of finding a set of Gabor filters and filter locations that distinguish all the positives from the negatives.

1.5.1 Genetic Algorithms

When the parameter space is vast (as it is in our case) a Genetic Algorithm (GA) searches for the optimum solution by randomly picking parameter sets and evolving newer ones from the best performers. This happens over many generations, hopefully resulting in the optimum set of parameters. To start the search, the GA generates a random set of *parents*. Each parent is characterized by the presence of a *chromosome*. The chromosome internally encodes all the parameters that are used by the parent to perform the intended operation. In our case, the intended operation is face recognition. The parent uses the parameters that are found in its chromosome to derive the Gabor features on the positive and negative images.

Based on the ability of these features to distinguish a face from all others in the database, the parent is ranked within its population. This rank is also referred to as the *fitness of the parent*. The ranking of all the parents, based on their fitness, marks the end of a generation, and a new generation needs to be created. New generations are formed based on three important aspects of GAs, *Retention*, *Cross Over* and *Mutation*. A portion of the newer generation is derived from the older generation, using the above mentioned methods, and the rest of the new generation is created randomly, maintaining the same overall number of parents between generations. Once a new population has been formed, the process of ranking parents occurs (as explained earlier) and a new generation is born out of that ranking. This iterative process continues until the parents in a certain generation are fit enough to achieve the given task (with the desired amount of success) or until the desired number of generations have evolved.

1.5.1.1 Use of Genetic Algorithms in Face Recognition GAs have been used in face recognition to search for optimal sets of features from a pool of potentially useful features that have been extracted from the face images. Liu et al [14] used a GA along with Kernel Principal Component Analysis (KPCA) for face recognition. In their approach, KPCA was first used to extract facial image features. After feature extraction using the KPCA, GAs were employed to select the optimal feature subset for recognition - or more precisely the optimal non-linear components. Xu et al [36] used GAs along with Independent Component Analysis to recognize faces. After obtaining all the independent components using the Fast ICA algorithm, a genetic algorithm was introduced to select optimal independent components.

Wong and Lam [35] proposed an approach for reliable face detection using genetic algorithms with eigenfaces. After histogram normalization of face images and computation of eigenfaces, the 'k' most significant eigenfaces were selected for the computation of the fitness function. The fitness function was based on the distance between the projection of a test image and that of the training-set face images. Since GAs are computationally intensive, the search space for possible face regions was limited to possible eye regions alone.

Karungaru et al [8] performed face recognition using template matching. Template matching was performed using a genetic algorithm to automatically test several positions around the target, and to adjust the size of the template as the matching process progressed. The template was a symmetrical T-shaped region between the eyes, which covered the eyes, nose and mouth.

Ozkan [18] used genetic algorithms for feature selection in face recognition. In this work, the Scale Invariant Feature Transform (SIFT) [15] was used to extract features. Since SIFT was originally designed for object recognition in general, genetic algorithms were used to identify SIFT features, which are more suitable to face recognition.

Huang and Weschler [6] developed an approach to identify eye location in face images using navigational routines, which were automated by learning and evolution using genetic algorithms. Specifically, eye localization was divided into two steps: (i) the derivation of the saliency attention map, and (ii) the possible classification of salient locations as eye regions. The saliency map was derived using a consensus between navigation routines that were encoded as finite state automata (FSA) exploring the facial landscape and evolved using genetic algorithms (GAs). The classification stage was concerned with the optimal selection of features and the derivation of decision trees for confirmation of eye classification using genetic algorithms.

Sun and Yin [23] applied genetic algorithms for feature selection in 3D face recognition. An individual face model was created from a generic model and two views of a face. Genetic algorithms were used to select optimal features from a feature space composed of geometrical structures, the labeled curvature types of each vertex in the individualized 3D model.

Sun et al [24] approached the problem of gender classification using a genetic algorithm to select features. A genetic algorithm was used to select a subset of features from a low-dimensional representation, which was obtained by applying PCA and removing eigenvectors that did not seem to encode information about gender.

As is evident from these citations, many feature-based approaches towards face recognition use genetic algorithms for feature selection. However, these approaches employ a single feature space derived from a set of face images. We believe that it is more effective to employ aimed at extracting person-specific features, and that an effective way to do this is by using genetic algorithms. As observed by [26], humans initially learn to recognize faces based on person-specific characteristic features. This suggests that better recognition performance might be achieved by representing each person's face in a person-specific feature space that is learned using GAs.

The following paragraphs describe how we employed GAs to solve the problem of finding person-specific Gabor features aimed at face recognition.

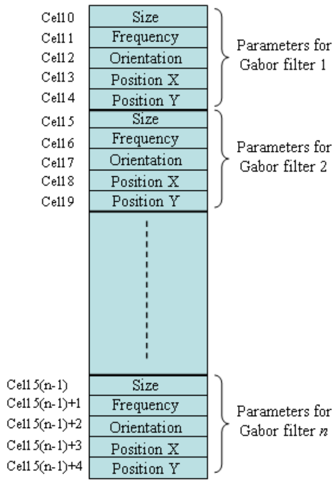


Fig. 1.4 A typical chromosome used in the proposed method.

1.5.1.2 The Chromosome Each parent per generation encodes the parameters of a set of Gabor filters in the form of a chromosome. In our implementation, each Gabor filter is represented by five parameters. If there are n Gabor filters, parameters for all of these filters are encoded into the chromosome in a serial manner, as shown in Figure 1.4. Thus the length of the chromosome is $5n$. The number of Gabor filters being used per face image determines the length of the chromosome. As shown in Figure 1.4, each parameter in the chromosome is encoded as a gene. The boundaries of these genes defines the regions where the chromosome undergoes both the crossover and mutation. The genes can be considered as the primary element of the parent responsible in the evolution.

1.5.1.3 Creation of the first generation Figure 1.5 depicts the first generation of parents, which are created randomly. Each parent's chromosome is filled randomly with parameter values where, each parameter value is within the allowed range for that parameter. Thus, in our experiment, each parent potentially has the parameters needed for it to perform face recognition using Gabor filters for feature extraction.

Once these parents are created, each parent in the gene pool is evaluated based on its capacity to perform face recognition. To this end, a fitness function is defined, which takes into account the ability of each parent to distinguish an individual from all others based on the most distinguishing features on the individual's face.

This fitness function also takes into account the similarity of the extracted features, and discourages the selection of features that are highly correlated

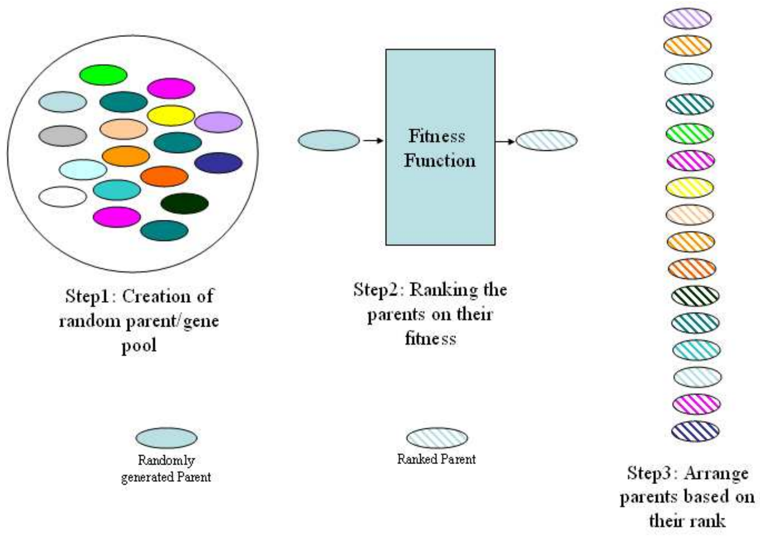


Fig. 1.5 Stages in the creation of the first generation of parents

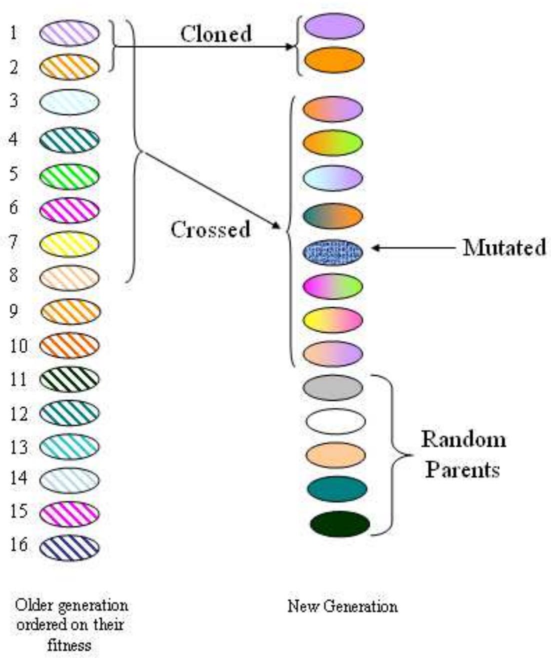


Fig. 1.6 Deriving newer parents from the current generation

with each other. This ensures that the face images will be searched for multiple distinguishing characteristics. Subsection 1.6.3.1 explains in detail the fitness function used in our experiments. The parents with the best fitness are ranked higher, and have the highest probability of being picked for using genetics the next generation. At the end of the rank ordering process, the parents are arranged in a descending order, based on their fitness. This rank ordering determines the probability of each parent being used to create the subsequent generation. If a parent has a higher fitness, it will have a higher probability of being cloned into the next generation, or of otherwise being involved in reproduction.

1.5.1.4 Creation of the newer generations The newer generations are created from the older population using *clones*, *mutants*, and *crossovers* of the fittest parents. To better search for the optimal parameter set, new random parents are created every generation. This reduces the likelihood that the algorithm will get stuck in a local minimum in the search space.

Figure 1.6 shows crossover creates a newer generation, using the fittest parents from the older generation.

The number of offsprings created from mutation, cloning, and crossover are determined by parameters of the Genetic algorithm. The number of clones, mutants, and corssovers are controlled by the following parameters:

1. *Cloning Rate* This parameter controls the number of parents from the previous generation that will be retained without undergoing any changes in their genetic structure.

2. *Crossover Rate* This parameter controls the number of offsprings that will be born from crossing the parents from the previous generation.

3. *Mutation Rate* This parameter determines how many of the crossed offsprings will then be mutated.

4. *Cloning Distribution Variance* After determining the number of offsprings be to cloned, the index of the parents for cloning are chosen using a normal distribution random number generator, with the mean zero and variance equal to this parameter. Since the parents from the previous generation have been rank ordered in descending order of fitness, the zeroth parent will be the top performer (which coincides with the mean of the random number generator, and has the highest probability of getting picked).

5. *Crossover Distribution Variance* This parameter (which is similar to the Cloning Distribution Variance) is used to choose the index of the parents who will undergo Crossover.

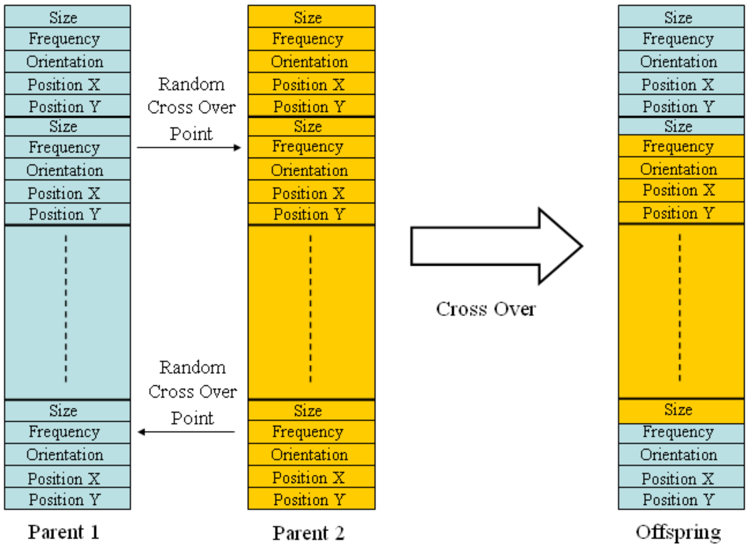


Fig. 1.7 Typical crossing of two parents to create an offspring

1.5.1.5 *Crossover* As discussed earlier, the parents for crossover are selected by a random number generator. Between these parents, the points of crossover are determined by choosing locations of crossover randomly. As seen in the Figure 1.7, these locations are arbitrary gene boundary locations and at these locations the gene content from the two parents gets mixed. The offspring thus created now contains parts of the genes coming from the contributing parents. The motivation for this step is the fact that, as more and more generations pass, the fittest parents undergoing crossover will already contain the better sets of parameters, and their crossing might bring together the better sets of parameter values from both the parents.

1.5.1.6 *Mutation* In addition to the process of crossover at gene boundaries in the chromosome, the values of some parameters within the genes might be changed randomly. This is illustrated in the Figure 1.8. Such mutations help in exploring the local parameter space more thoroughly. Mutations can be seen as small perturbations to the larger search that explores the vast parameter space, searching for the global minima.

1.6 METHODOLOGY

Most feature-based face recognition methods use feature detectors that are not tailored specifically for face recognition, and they make no attempt to

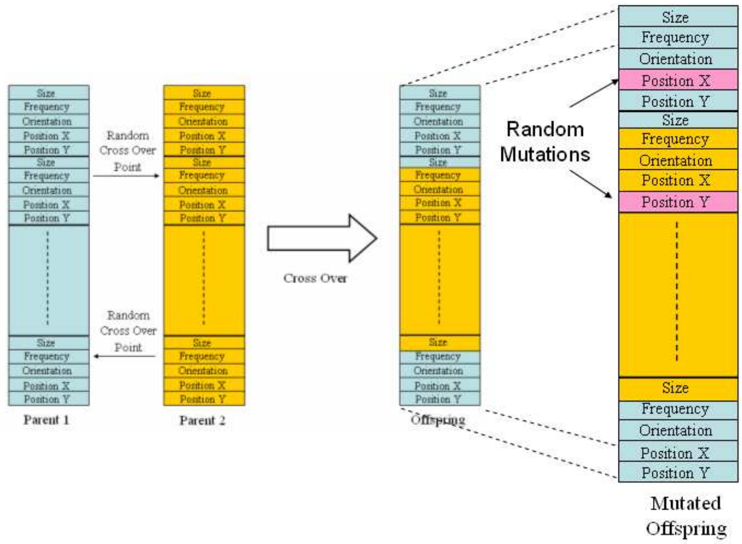


Fig. 1.8 Mutation of a newly created offspring

selectively choose feature detectors based specifically on their usefulness for face recognition. The method described in this paper uses Gabor wavelets as feature detectors, but evaluates the usefulness of each particular feature detector (and a corresponding (x, y) location) for distinguishing between the faces within our face database. Given the very large number of possible Gabor feature detectors and locations, we use a Genetic Algorithm (GA) to explore the space of possibilities, with a fitness function that propagates parents with a higher ability to distinguish between the faces in the database. By selecting the Gabor feature detectors and locations that are most useful for distinguishing each person from all of the other people in the database, we define a unique (i.e. person-specific) feature space for each person.

1.6.1 The FacePix (30) Database

All experiments were conducted with face images from the FacePix (30) database [3]. FacePix(30) was compiled to contain face images with pose and illumination angles annotated in 1 degree increments. Figure 1.9 shows the apparatus that is used for capturing the face images. A video camera and a spotlight are mounted on separate annular rings, which rotate independently around a subject seated in the center. Angle markings on the rings are captured simultaneously with the face image in a video sequence, from which the required frames are extracted.

Fig. 1.9 The data capture setup for FacePix(30)

This database has face images of 30 people across a spectrum of pose and illumination angles. For each person in the database, there are three sets of images. (1) The *pose angle set* contains face images of each person at pose angles from $+90^o$ to -90^o (2) The *no-ambient-light set* contains frontal face images with a spotlight placed at angles ranging from $+90^o$ to -90^o with no ambient light, and (3) The *ambient-light set* contains frontal face images with a spot light placed at angles placed at angels from $+90^o$ to -90^o in the presence of ambient light. Thus, for each person, there are three face images available for every angle, over a range of 180 degrees. Figure 1.10 provides two examples extracted from the database, showing pose angles and illumination angles ranging from -90^o to $+90^o$ in steps of 10^o. For earlier work using images from this database, please refer [12]. Work is currently in progress to make this database publicly available.

We selected at random two images out of each set of three frontal (0^o) (Figure 1.11) images for training, and used the remaining image for testing. The genetic algorithms used the training images to find a set of Gabor feature detectors that were able to distinguish each person's face from all of the other people in the training set. These feature detectors were then used to recognize the test images.

In order to evaluate the performance of our system, we used the same set of training and testing images with face classification algorithm based on low-dimensional representation of face images extracted through Principal Com-

Fig. 1.10 Sample face images with varying pose and illumination from the FacePix(30) database

(a) (b) (c)

Fig. 1.11 Sample frontal images of one person from the FacePix(30) Database

ponent Analysis [22]. Specifically, the performance of the implementation of PCA-based face recognition followed by [27] was used in our experiments.

1.6.2 The Gabor Features

Each Gabor feature corresponds to a particular Gabor wavelet (i.e. a particular special frequency, a particular orientation, and a particular Gaussian-defined spatial extent) applied to a particular (x, y) location within a normalized face image. (Given that 125 different Gabor filters were generated, by varying ω, σ and θ in 5 steps each, and given that each face image contained $128 \times 128 = 16,384$ pixels, there was a pool of $125 \times 16384 = 2,048,000$ potential Gabor features to choose from.) We used an N-dimensional vector to represent each person's face in the database, where N represents the predetermined number of Gabor features that the Genetic Algorithm selected from this pool. Figure 1.12 shows an example face image, marked with 5 locations where Gabor features will be extracted (i.e. N = 5). Given any normalized face image, real number Gabor features are extracted at these locations using Equation 1.6. This process can be envisioned as a projection of

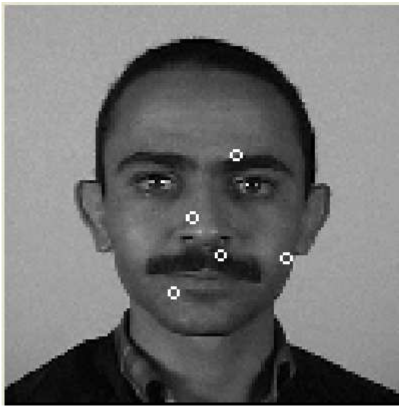


Fig. 1.12 A face image marked with 5 locations where unique Gabor features were extracted

a 16,384-dimensional face image onto an N dimensional subspace, where each dimension is represented by a single Gabor feature detector.

Thus, the objective of the proposed methodology is to extract an N dimensional real-valued person-specific feature vector to characterize each person in the database. The N (x, y) locations (and the spatial frequency and spatial extent parameters of the N Gabor wavelets used at these locations) are chosen by a GA, with a fitness function that takes into account the ability of each Gabor feature detector to distinguish one face from all the other faces in the database.

1.6.3 The Genetic Algorithm

Every GA is controlled in its progress through generations with a few control parameters such as,

- the number of generations of evolution (n_g)
- the number of parents per generation (n_p)
- the number of parents cloned per generation (n_c)
- the number of parents generated through cross over (n_{co})
- the number of mutations in every generation (n_m)

In our experiments, the GA used the following empirically-chosen GA parameters: $n_g = 50$, $n_p = 100$, $n_c = 6$, $n_{co} = 35$ and $n_m = 5$.

1.6.3.1 The Fitness Function The fitness function of a genetic algorithm determines the nature of the search conducted over the parameter space. For face recognition applications, the fitness function is the capacity of a parent to classify the individuals accurately. In our proposed method, the fitness function needs to take both the Gabor features and the corresponding feature locations into consideration when evaluating face classification. We define here a fitness function that has two components to it. One determines the capacity of the parent to isolate an individual's face image from the others in the database, and the other evaluates whether the feature is redundant with other extracted features (i.e. whether a feature detector produces coefficients that are highly correlated with the coefficients produced by another feature detector.) Thus the fitness F can be defined as

$$F = w_D D - w_C C \tag{1.7}$$

where D is the distance measure weighted by w_D, and C represents the correlation measure which measure the similarity between the coefficients that have been extracted. The correlation measure C is weighted by the factor w_C.

If a parent extracts features from a face image that distinguish one individual from all the others very well (compared to the other parents within the same generation) then the distance measure D will be the largest for that parent, making its fitness F large. If the correlation between the extracted features is small, C will be small, which also makes the fitness F large. Thus, the correlation measure serves as a *penalty* for extracting the same feature from the face image multiple times, even though that particular feature might be the best distinguishing feature on that face.

The correlation between coefficients was used instead of spatial separation to counter the problem of similar features being extracted, because the Gabor filters might not be able to represent the underlying image characteristic completely. If there are some large image features on the face (such as beard) that require multiple Gabor features within a certain spatial locality. Setting a hard lower limit on this spatial separation might lead to insufficient representation of that large image feature, in terms of the Gabor filters.

Consider a parent searching for a unique set of M Gabor filters to distinguish one individual's face from all other faces. Let this set of filters be referred to as S. Thus, $S = \{G_1, G_2, \cdots, G_M\}$ where, G_m represents the m^{th} Gabor filter.

If the set all individuals in the database is referred to as $I = \{i_1, i_2, \cdots, i_j\}$ with J number of individuals, then for every individual i in I a set S_i has to be extracted. To achieve this, all the images in the database depicting individual i are marked as positives, and the ones not depicting that individual are marked as negatives. Let the set of positive images be referred to as P_i (with L number of images) and the set of negatives be referred to as N (with K number of images). Thus, $S_i = \{G_{1i}, G_{2,i}, \cdots, G_{mi}\}$, $P_i = \{p_{1i}, p_{2i}, \cdots, p_{li}\}$

and $N_i = \{n_{1i}, n_{2i}, \cdots, n_{ki}\}$ are the sets of Gabor filters, positive images and negatives images set respectively for the individual i.

- **The Distance Measure** D
  A parent trying to recognize an individual i with a Gabor filter set S_i can be thought of as a transformation that projects all of the face images from the image space to a M-dimensional space, where the dimensions are defined by the M Gabor filters in the set S_i. Thus, all of the images in the two sets P_i and N_i can be considered as points on this M-dimensional space. Since the goal of the genetic algorithm is to find the set S_i which best distinguishes the individual i from others, in our method we search for the M dimensional space (defined by a parent) that best separates the points formed by the sets P_i and N_i. Figure 1.13 is an illustration of hypothetical set of face images projected on a 2 dimensional space defined by a set of 2 Gabor filters $S_i = \{G_0, G_1\}$. As shown in the figure, the measure D is the minimum of all the Euclidian distances between every positive and negative points.

  Thus, D can be defined as follow:

  $$D = \min_{\forall \ l,k} \left[\delta_M \left(\phi_M(p_{li}), \phi_M(n_{ki}) \right) \right] \tag{1.8}$$

  where,
  $\delta_M(A,B) = \sqrt{(a_1-b_1)^2 + (a_2-b_2)^2 + \cdots + (a_m-b_m)^2}$ is the M-dimensional Euclidian distance between A and B. a_x and b_x corresponds the x^{th}-coordinate of A and B respectively
  $\phi_M(X)$ is the transformation function that projects image X from the image space to the M-dimensional space defined by the set of Gabor filters.

- **The Correlation Measure** C
  In the proposed method, in addition to having every parent selecting the Gabor filter set S_i that can best distinguish the individual i from all the others in the database, it is necessary to ensure that this set of Gabor filters does not include filters that extract identical image features. If there were no such constraint, the algorithm might find one very distinguishing image feature on the face image and, over generations of evolution, all of its Gabor filters might converge to this one image feature. To avoid this, the correlation measure C determines the correlation between the image features extracted at all the locations pointed to by the chromosome. To test for correlations between the Gabor features at the different spatial locations, we use the entire set of 125 Gabor filters to thoroughly characterize the textural context at these locations.

  Assuming that there are M Gabor features that we are looking for on the face image of individual i, let $(x_m, y_m), m = 1, 2, \ldots, M$ be the M points that have been selected genetically in the chromosome. To find

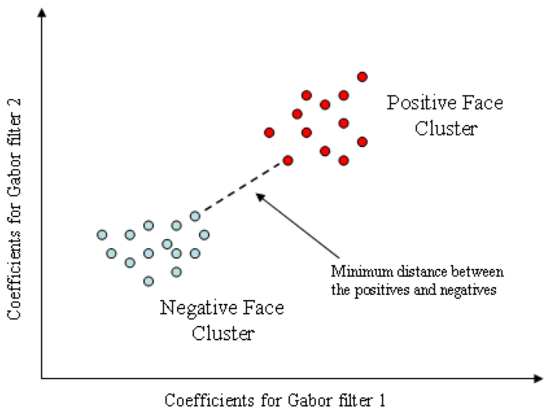


Fig. 1.13 Distance Measure D for the fitness function

the correlations of the image features extracted at each of these points, the N Gabor filters $G_i, i = 1, 2, \ldots, N$ are used to characterize each of the points. Let the coefficients of such a characterization be represented by a matrix A. Thus, matrix A is $M \times N$ in dimension, where the rows correspond to the M locations and $N = 125$ refers to the Gabor filter coefficients. Thus,

$$A = \begin{bmatrix} g_{(1,1)} & g_{(1,2)} & \cdots & g_{(1,N)} \\ g_{(2,1)} & g_{(2,2)} & \cdots & g_{(2,N)} \\ \vdots & \vdots & \vdots & \vdots \\ g_{(m,1)} & g_{(m,2)} & \cdots & g_{(m,N)} \end{bmatrix} \tag{1.9}$$

where, $g_{(m,n)}$ is the coefficient obtained by applying the n^{th} Gabor filter to the image at the point (x_m, y_m).

The Correlation measure can now be defined in terms of matrix A as follows

$$C = \log\left(\det\left(diag(B)\right)\right) - \log\left(\det(B)\right) \tag{1.10}$$

where, $diag(B)$ returns the diagonal matrix corresponding to B, and B is the covariance matrix defined by $B = \frac{1}{N-1}(AA^T)$.

Examining the Equation 1.10, it can be seen that the first log term gets closer to the second log term when the off diagonal elements of B reduces. The diagonal elements of the matrix B corresponds to the variance of the M image locations, whereas the off diagonal elements correspond to the covariance between pairs if locations. Thus, as the covariance between the image points decreases, the value of the overall correlation parameter decreases.

- **Normalization of D and C**
  In order to have an equal representation of both the Distance measure D and the Correlation term C in the fitness function, it is necessary to normalize the range of values that they can take. For each generation, before the fitness values are used to rank the parents, parameters D and C are normalized to range between 0 and 1.

$$D_{norm} = \frac{D - D_{Min}}{D_{Max} - D_{Min}} \tag{1.11}$$

$$C_{norm} = \frac{C - C_{Min}}{C_{Max} - C_{Min}} \tag{1.12}$$

  where, the Max represents the maximum value of D or C in a single generation across all the parents and Min refers to the minimum value.

- **Weighting factors w_D and w_C**
  The influence of the two components of the fitness function are controlled by the weighting factors w_D and w_C. We used the relation $w_C = 1 - w_D$ to control the two parameters simultaneously. With this relationship, a value of $w_D \approx 1$ will subdue the effect of the Correlation measure, causing the genetic algorithm to choose the Gabor filters on the most prominent image feature alone. On the other hand, $w_D \approx 0$ will subdue the Distance measure, deviating the genetic algorithm from the main goal of face recognition. Thus an optimal value for the weight w_D has to be estimated empirically, to suit the face image database in question.

1.7 RESULTS

To evaluate the relative importance of the two terms (D and C) in the fitness function, we ran the proposed algorithm on the training set several times with 5 feature detectors per chromosome, while changing the weighting factors in the fitness function for each run, setting w_D to 0, .25, .50, .75, and 1.00, and computing $w_C = (1 - w_D)$. Figure 1.14 shows the recognition rate achieved in each case.

We then ran the proposed algorithm on the training set 5 times, while changing the number of Gabor feature detectors per parent chromosome for each run to 5, 10, 15, 20, and 25. In all the trials, w_D=0.5. Figure 1.15 shows the recognition rate achieved in each case.

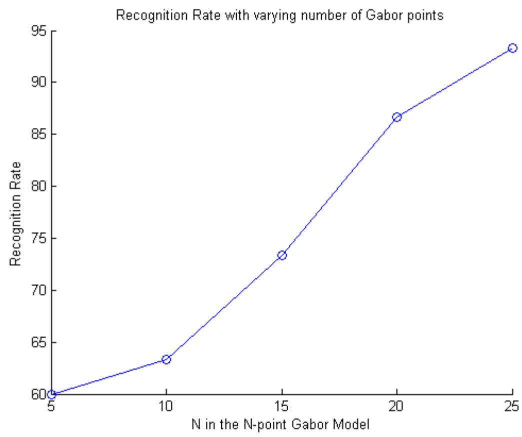


Fig. 1.14 The recognition rate versus the number Gabor feature detectors

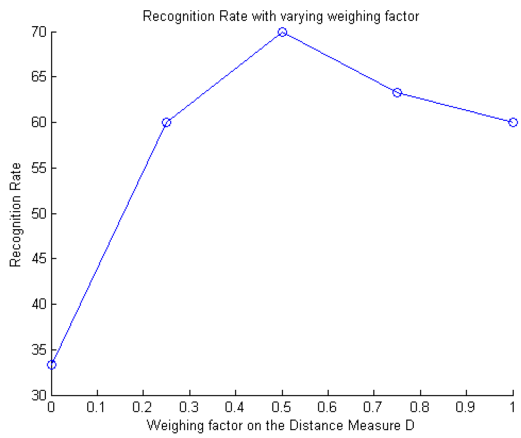


Fig. 1.15 Recognition rate with varying w_D

1.7.1 Discussion of Results

Figure 1.14 shows that the recognition rate of the proposed algorithm when trained with 5, 10, 15, 20, and 25 Gabor feature detectors increases monotonically, as the number of Gabor feature detectors (N) is increased. This can be attributed to the fact that increasing the number of Gabor features essentially increases the number of dimensions for the Gabor feature detector space, allowing for greater spacing between the positive and the negative clusters.

Figure 1.15 shows that for N = 5 the recognition rate was optimal when the distance measure D and the correlation measure C were weighted equally, in computing the fitness function F. The dip in the recognition rate for $w_D = 0.75$ and $w_D = 1.0$ indicates the significance of using the correlation factor C in the fitness function. The penalty introduced by C ensures that the GA searches for Gabor features with different textural patterns. If no such penalty were be imposed, the GA might select Gabor features that are clustered on one salient facial feature, such as a mole.

The best recognition results for the proposed algorithm (93.3%) were obtained with 25 Gabor feature detectors. The best recognition performance for the PCA algorithm was reached at about 15 components, and flattened out beyond that point, providing a recognition rate for the same set of faces that was less than 83.3%. This indicates that, for the face images used in this experiment (which included substantial illumination variations) the proposed method performed substantially better than the PCA algorithm.

1.7.2 Person-specific feature extraction

When the FacePix(30) face database was built, all but one person were captured without eyeglasses or a hat. Figures 1.16(a) and 1.16(b) show the results of extracting 10 and 20 distinguishing features from that person's face images. The important things to note about these results are:

1. At least half of the extracted Gabor features (8 of the 10) and (10 of the 20) are located on (or near) the eyeglasses.

2. As the number of Gabor features was increased from 10 to 20, more Gabor features are seen toward the boundaries of the images. This is due to the fact that the genetic algorithm chooses Gabor feature locations based on a Gaussian probability distribution that is centered over the image, and decreases toward the boundaries of the images.

These results suggest that person-specific feature extraction might be useful for face recognition in small face databases, such as those typical of a social interaction assistance device for people who are blind.

(a) (b)

Fig. 1.16 10 and 20 person-specific features extracted for a particular individual in the database

1.8 CONCLUSIONS AND FUTURE WORK

As mentioned earlier, the proposed person-specific approach to evolutionary feature selection in face images is well-suited for applications such as those that enhance social interaction for people who are blind, because people do not generally disguise their appearance in normal social situations, and even when some significant change occurs (such as a man shaving off his beard) the system can continue to evolve as it captures new images with each encounter.

A wearable social interaction assistant prototype has been implemented using a pair of eyeglasses equipped with a tiny unobtrusive video camera in the nose bridge [10] and is shown in Figure 1.17. The analog video output from this camera is passed through a video digitizer, and the resulting digital stream is then fed into a portable laptop computer. A video stream is captured of any person standing in front of the eyeglasses. A face detection algorithm, based on Adaboost [28], is then used to identify the frames of the video where a face is present, and to localize that face within that frame. This detected face is then cropped and compared to indexed faces in a face database.

The performance of the proposed approach for identifying person-specific features relies, to a large extent, on obtaining near-frontal views of faces. To offset this limitation, there is ongoing work [1] to perform person-independent head pose estimation on the face images obtained from this platform. It is expected that this will help us select face images from the video stream with near-frontal views, which will improve the performance of our algorithm in identifying person-specific features.

Another factor that limits the performance of our algorithm is illumination variations in the captured images. Especially problematic are variations between outdoor-indoor and day-night settings. (Of course, this limitation is not unique to our algorithm.) As a strategy to provide additional light unobtrusively under adverse lighting conditions, we are employing infra-red LED illuminators in conjunction with an infrared-sensitive camera.

In summary, while there have been many different feature-based approaches to face recognition over the last two decades of research, we have proposed a novel methodology based on the discovery and extraction of person-specific

Fig. 1.17 Wearable face recognition platform

characteristic features to improve face recognition performance for small face databases. This approach is aimed at facilitating social interaction in casual settings. The use of Gabor features, in tandem with a genetic algorithm to discover characteristic person-specific features has been inspired by the human visual system and is based on knowledge that has been developed about the process by which humans recognize faces. We believe that more needs to be learnt about human face recognition, and that as more is learnt, the knowledge can be put to use to develop more robust face recognition algorithms.

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