Face recognition by means of facial parameters and finding feature points in an image

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Abstract
Since identification is one of the important issues in today's societies, many methods were presented for biometric identification. One of these identification methods is face recognition. There are different facial features in different individuals. Many algorithms were presented to find feature points in an image the best of which to name is the SIFT algorithm because this algorithm is resistant to image scaling and rotation which are important challenges in image processing. In this paper, using the SIFT algorithm, a new method was presented for face recognition which has a better performance compared to previous face recognition methods.

Key words:
Identification and authorization, Biometric identification, Feature extraction.

1 Introduction

A person's face plays a fundamental role in identification and expression of feelings in a society and the human ability in face recognition is remarkable. This ability is resistant to changes in facial expression, age, and also changes in eyeglasses, beard or hair style. In recent years, face recognition has been greatly researched in studies related to biometrics, pattern recognition and machine vision.Face recognitions methods are also used in some commercial and security applications.These applications include security control of individuals, access control, identification of criminals (e.g. for passports), face reconstruction and human-computer interfaces. Face recognition methods can be categorized into three categories: 1) methods which consider the overall features of a face, 2) methods which are based on a model and consider the texture of some parts of a face, and 3) combined methods which use both said methods.
A complete study on identification methods using two-dimensional imageswas performed by Zhao et al. [1].The most popular first class method is Eigenface proposed by Turk &Pentland which uses the main element analysis method [2]. The Fisherface method which uses the analysis of linear separation [3], Bayesian method [4], SVM [5] and neural network methods [6] are other methods which use an entire face for identification. Of second class (model-based) methods, the Elastic Bunch Graph [7] and Active Appearance Model [8] can be mentioned. A third class methods is a method which uses a combination of Eigenface, Eigennose and Eigeneye [9].
In this paper, a new method based on SIFT is proposed. Next the new method is compared with the algorithms of Eigenfaces and Fisherfaces which shows that this method provides better results compared to two other methods. In the following, in section 2, we describe past studies performed in this area and in section 3, we will explain the SIFT algorithm and how it works and then in sections 4 and 5, we will investigate and assess the proposed method and in section 6, we will provide the conclusions.

2 Research background

In a paper in 1991 in which the Eigenfaces algorithm was presented by Turk et al. [2] which is based on the dimensionality reduction method of principal component analysis (PCA), the main idea was to use each image as a vector in a space with high dimensions. For the input image in this method, first the image is transferred using an eigenvectors matrix or subspace comprising vectors. Next, in the space which underwent dimensionality reduction, it is compared with existing data and the most similar image is selected as the identified method. In this method, first the data covariance matrix and then the vectors matrix and eigenvalues are calculated. The eigenvectors matrix is composed of orthogonal vectorswhich constitute the feature subspace and by transferring the data to these subspaces, the data become independent. Each input image can be displayed as a linear combination of these Eigenfaces through the introduction of the image on the new Eigenfaces space.The input image is identified for conversion to the eigenspace, and the most similar image is selected as the identified image using the nearest neighbor.Two types of nearest neighbors are used for clustering in the procedure. The first input image is compared with the entire image in the database. Next, the nearest cluster center is obtained. Finally, a calculation is performed using each cluster (the face of a person) and that cluster is selected for comparison.

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The Fisherfaces is based on linear discriminant analysis (LDA) in face recognition. The objective is to generate a space in whichintra-class distribution and inter-class distribution are minimum and maximum, respectively. Also finding some vectors to provide the best classes for separation, is an attempt to maximize the difference between the classes and minimize their classes. This algorithm works like PCA. Each facial image is considered as a point in a space with high spaces. Next, data LDA applies a new base for vectors, and this method is called Fisherfaces. Accordingly, facial images are used for matching.

3 The SIFT algorithm

Scale Invariant Feature Transform (SIFT) is an algorithm in machine vision used to extract specific features from images, and it is also used in algorithms of tasks such as matching different views of an object or scene (e.g. in binoculars) and object identification [10]. Acquired features are invariant to image scale and rotation and they are also somehow invariant to view changing and lighting changes. These features are extracted within four stages. In the first stage, using the Gaussian filter, all the image points in all scales are searched to find features invariant to changed direction and scale. In the next stage, in each potential point, an extended model is used to determine appropriate points based on different sustainability criteria. In the next stage, based on the local image gradient in the desired points, a direction towards each feature point is allocated. Finally, the information existing in the Gradient function around the feature points is codified somehow and used as the characteristic of each feature for subsequent tasks such as feature matching. The name of this descriptor was selected due to the fact that it converts the image data algorithm to scale coordinates which are independent from the local features.Each feature of a vector is considered of the dimension 128 identified in the neighborhood of the identified key point.

4 Proposed framework

In this paper, a new method based on the SIFT descriptor was proposed for face recognition. The SIFT descriptor uses an entire image in a database for feature extraction. Next, based on a new facial image, the features extracted from that face are compared with some features of each face in the database. Finally, a facial image with the greatest number of points matching the most similar face is used for facial categorization.

In the proposed method, a compatible feature is considered for comparison with another feature when the distance of that feature is less than a certain deduction of the distance of the next nearest feature. Doing so will reduce the number of incorrect matches. Regarding the incorrect matches, a number of other near features with near distances exist based on high dimensions of existing features. However, if a correct match is found, finding its other feature is unlikely given the highly distinctive nature from the SIFT descriptor.

5 Assessment and investigation of the proposed framework

5.1 Database of the proposed framework

Two databases are used in the proposed framework. The first database is the AT&T database which includes 400 images of 40 persons with 10 different images per person. In this database, there are different facial directions and impressions for every person. The image size is 92*112 pixels. On average, 70 SIFT features are extracted from each image.

The second face database, is the Yale database. This database includes 165 images of 15 persons with 11 images per person. The images contain different facial impressions and lighting conditions for every person. The size of the images is 243 * 320 pixels and on average, 230 SIFT descriptors are extracted for every image. Figure 1 shows an example of images of this database. 5 sample images of faces are shown with the SIFT descriptor which is shown with +. The primary faces were used without any preprocessing in the assessment of the algorithm strength in the comparison.

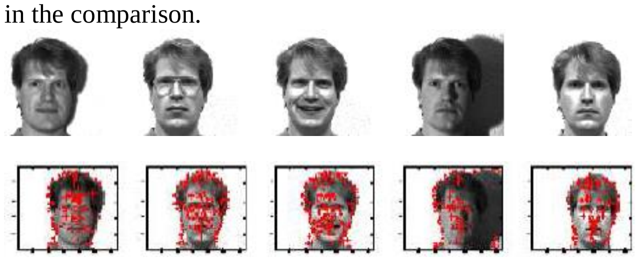

Fig. 1 an example of images presented with the application of the SIFT descriptor on them

5.2 Comparing the proposed framework with other methods

In order to evaluate the proposed algorithm, the new method is compared with both methods of Eigenfaces and Fisherfaces. Ten independent executions were performed where the total data was randomly divided into two halves, one for training and the other for testing. The results of this introduction, shows the mean of these executions. Three distance criteria were used for Eigenfaces and Fisherfaces:

Euclidean distance: $d(x,y) = \sqrt{\sum_i (x_i, y_i)}$

City-block distance: $d(x,y) = \sum_i \|x_i - y_i\|$

Cosine distance: $d(x, y) = \frac{xy}{\|x\|_2 \|y\|_2}$

Where x and y are two feature vectors and $\|0\|_2$ is the mediocrity of the Euclid. The nearest neighbor and nearest cluster center of the neighbor with two algorithms were used.Also two distance criteria were used for matching the SIFT features: the cosine distance and angle distance are definedas $d(x, y) = \cos^{-1}(x, y)$.

The results obtained from comparing the three methods are shown in table 1. Table 1 clearly shows the efficiency of the SIFT method compared to the other two methods. The results of the SIFT descriptor in the Yale database was 93.8% compared to 73.1% for Eigenface and 88.1% for Fisherfaces. Also the results show that the city-block distance is generally better for Eigenface and Fisherfaces, whereas the angle distance is better for the SIFT descriptor.

Table 1: comparing the proposed method with the two methods above (the best results are highlighted)

	Eigenfaces					
	Nearest Neighbor			Nearest Cluster Center		
	Euclidean	City-block	Cosine	Euclidean	City-block	Cosine
AT&T	89.3	92.9	89.5	74.9	87.1	75.7
Yale	68.7	72.2	68.4	57.7	73.1	59.8
	Fisherfaces					
	Nearest Neighbor			Nearest Cluster Center		
	Euclidean	City-block	Cosine	Euclidean	City-block	Cosine
AT&T	91.3	91.8	93.8	91.4	91.1	94.7
Yale	83.4	86.1	68.2	83.8	88.1	84.6
	SIFT					
	Cosine			Angle		
AT&T	93.9			96.3		
Yale	86.8			93.8		

5.3 Assessing the size of the training set

In order to assess the performance of the different sizes of the training set, two tests were performed. The first test was performed using a training set of 20% and a testing set of 80%. The second testwas performed using a training set of 80% and a testing set of 20%. In all the tests, 10 independent tests with random selection from the training and testing sets were performed.

Table 2 shows the results from the tests. As expected, efficiency gets decreased with the smaller training dataset and increased with the larger training set.Also the SIFT descriptor method is better than other methods. Efficiency in the Yale database using a set of smaller trainings is significantly better (90.3% for SIFT compared to 73.3% for Eigenfaces and 83.5% for Fisherfaces).

Table 2: results of the size of the training dataset

	Eigenfaces					
	Nearest Neighbor			Nearest Cluster Center		
	Euclidean	City-block	Cosine	Euclidean	City-block	Cosine
AT&T 20%	77.2	83.1	78.1	71.9	89.2	72.0
Yale 20%	69.5	73.3	72.0	58.9	69.9	62.9
AT&T 80%	96.0	97.8	95.6	78.6	91.3	76.4
Yale 80%	81.5	83.5	81.0	70.1	78.9	76.2
	Fisherfaces					
	Nearest Neighbor			Nearest Cluster Center		
	Euclidean	City-block	Cosine	Euclidean	City-block	Cosine
AT&T 20%	76.8	74.7	84.6	79.2	77.4	85.0
Yale 20%	83.4	82.3	82.3	83.5	82.5	83.0
AT&T 80%	95.3	94.1	96.7	95.7	94.6	96.4
Yale 80%	87.0	89.6	89.3	87.0	89.6	89.3
	SIFT					
	Cosine			Angle		
AT&T 20%	79.7			85.7		
Yale 20%	86.7			90.3		
AT&T 80%	99.0			99.5		
Yale 20%	92.2			95.9		

5.4 A number of SIFT features

When trying to evaluate a significant number of SIFT features required for a reliable matching of facial images, several tests were performed using a subset of the SIFT features extracted in the matching process.

The SIFT features are classified downwards according to their scale. Only P% of the mean of the number of features was used. We used a P of 5%to 100% with an increment from 5.Figure 2 shows the results for the Yale database. On average, these results are obtainedindependently after ten executions using a training dataset of 50% and testing dataset of 50%. It is clear that the accuracy increases with the increased number of used SIFT features. Only a 30% use of the characteristics gives a better accuracy compared to Eigenfaces and Fisherfaces. This significantly reduces the execution time in the matching process for SIFT, as a number of matching operations in O(n2) in which n is the number of features for matching. Using only 30% of the features, only 9% of the time is used to match all the points.

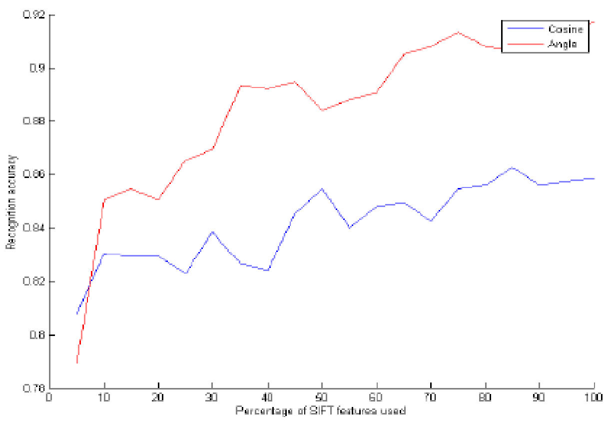

Fig. 2 A number of important SIFT features in the Yale database

5.5 Resolution of facial images

In order to investigate sampling from facial images for SIFT feature matching, a number of experiments with different sizes of facial images were performed and a report of the accuracy and correctness was provided. The primary size of the image was reduced to 75%, 50% and 25% of the original size. It was performed independently ten times and using random analysis, we divided the data into two halves

Table 3 shows the acquired results. It is clear that the number of SIFT features decreases with decreased extracted image resolution. However, up to 50%, the solutions provided results comparable with all the scales, whereas in 25%, the accuracy significantly decreases. In fact, the results of resolutions up to 50% are still better than Eigenfaces and Fisherfaces.

Table 3: image resolution (accuracy)

	AT&T			Yale		
Resolution	#SIFT	Cosine	Angle	#SIFT	Cosine	Angle
100%	72	94.7	97.3	233	86.1	93.0
75%	55	93.6	96.6	157	88.4	92.6
50%	33	95.8	95.0	90	88.0	93.7
25%	12	88.6	89.2	38	80.0	83.6

6. Conclusion

In this paper, a new method was presented for face recognition based on SIFT features. The results in all the experiments show that the new method provides better results compared to Eigenfaces and Fisherfaces with smaller training data. After investigating an effective number of SIFT features required for reliable matching, the experiments show that only 30% of the features which save 91% of the time for matching with all the extracted features are used. Moreover, the SIFT features presented a better performance for resolution reduction up to 50%.

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