Face Identification with Modified K-NN Classifier Based on Linear and Angular Distance

Agata H. Manolova[1] and Roumen K. Kountchev[2]

Abstract – **Visual recognition systems use characteristic portions of the human body for identification purposes – like the face. This paper proposes a novel face identification method which exploits the global discriminative features of the human face. In this method, global features are extracted from the whole face images by keeping the low-frequency coefficients of 2D Mellin-Fourier transform. This transform ensures that the face representation is invariant to scale, rotation, translation and significant contrast and illumination changes. After that, to the feature vector of each face, a modified K-Nearest Neighbours classifier with Euclidean and cosine angle distance is applied. We evaluate the proposed method using one large-scale face database. Experiments show that the results of our method are very good for identifying a given human face.**

Keywords – **Face identification, K-NN classifier, cosine angle distance, 2D Mellin-Fourier transform.**

I. Introduction

The field of biometrics involves identifying people by measuring parts of their bodies. It now promises to find wide acceptance as a convenient and secure alternative to typed passwords, mechanical keys, or written signatures for access to computers, facilities or vehicles, and identification for financial transactions. Personal access control systems have been implemented using visual recognition for identification of individuals. Typical of this type of access control are face recognition systems and fingerprint recognition systems. Image recognition, and particularly face recognition, is becoming an increasingly popular feature in a variety of applications. Face recognition applications can be used by security agencies, law enforcement agencies, the airline industry, the border patrol, the banking and securities industries and the like.

There are two predominant approaches to the face recognition problem: geometric (feature based) and photometric (view based) methods. The feature-based techniques use edge information, skin color, motion, symmetry, feature analysis, snakes, deformable templates and point distribution. Image-based techniques include neural networks, linear subspace methods like eigen faces. The most well studied algorithms for face identification in the literature are the Principal Component Analysis, the Independent Component Analysis, the Linear Discriminant Analysis, the Elastic Bunch Graph Matching, Kernel Methods, the Active Appearance Model and the Support Vector Machines. Given these numerous theories and techniques that are applicable to face recognition, a detailed evaluation and benchmarking of these algorithms is given in [1] and [2].

We have developed an automatic approach for one-to-one face matching that is capable to recognize an input facial image in a given database of images. This method for face identification is based on the extraction of the low-frequency coefficients from the whole face image and a modified K-Nearest Neighbors algorithm with Euclidean and angular distance, applied on the feature vectors for comparison. The current work is divided in three steps:

The first part consists of image pre-processing for the needs of the algorithm;

The second step is the development of the algorithm for face identification - the extraction of the feature vector of each face image of the database and the matching algorithm;

The last part includes the implementation of the method, applied on a face image database with 450 JPEG images with 31 faces with different lighting/expressions/backgrounds from the Computational Vision at CALTECH [3].

II. Development of the Face Identification Algorithm

A. Face Image pre-processing

For the needs of the proposed algorithm, there are some necessary pre-processing steps for the face images before the matching step is applied. The first step of the pre-processing is the development of an application for segmentation of the face by a skin color segmentation method combined morphological filtering as proposed in [4]. We also apply a filtering by object dimensions to be able to separate the face from any other non relevant objects with skin color. Then a rectangular frame is cut around the segmented area with the face. After that the segmented rectangular frame is transformed in greyscale i.e. a conversion from the RGB color space to the YCbCr model where we keep the Y component. The second important condition is that all the images in the database must have the same height / weight m ($m = 2^n$ and $n \in$ IN) so we apply the standard nearest neighbor interpolation algorithm on the rectangular frame. An example of this application is shown on Fig. 1.

B. The feature vector extraction

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The next step is the feature vector extraction for each segmented face and the creation of the feature vector database.

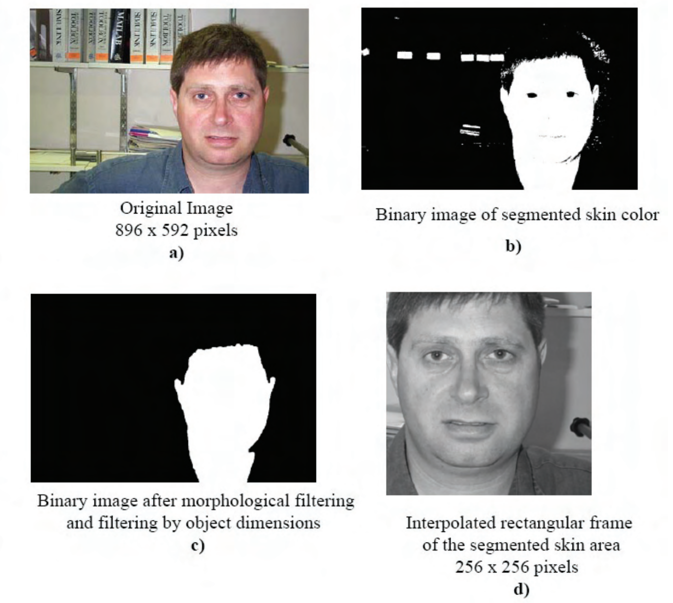


Fig. 1 Example of the pre-processing stage of the algorithm.

The idea of the method is to represent the image by a small number of meaningful coefficients that describe it at various resolution levels, and which also encode spatial relationships between various image components, by virtue of the space-frequency localization property of the wavelet transform. Meaningful coefficients can be extracted through vector quantization procedures, or by selectively picking those with the largest magnitude. Although these methods successfully address the multiple-feature integration problem, they suffer from a major weakness, namely their lack of invariance to translation and rotation, and, to a lesser extent, to scale changes. If a set of images of the same subject contains object in motion, it will be therefore difficult to recognize the object if a standard algorithm is used.

Face recognition depends heavily on the particular choice of features so we use the 2D Mellin – Fourier transform witch allows us to extract the global features from the whole face by keeping the low-frequency coefficients of 2D Mellin-Fourier transform, which we believe encodes the holistic facial information, such as facial contour. This transform ensures also, that the face representation is invariant to scale, rotation, translation and significant contrast and illumination changes [5], [6]. Experimental results on real gray-level images show that it is possible to recover an image to within a specified degree of accuracy and to classify objects reliably even when a large set of descriptors is used [7]. The feature vector extraction algorithm includes the following steps:

1. To the halftone image of Fig. 1 d) a 2D Fourier transform is applied then the magnitude specter is centered and a binary square mask (32 x 32) is applied to retain only the low-frequency coefficients at the center (Fig. 2 a) and b)). The first 2D FFT achieves translation invariance ;
2. To achieve invariance to rotation and scale transformation we perform further non-linear and non-invertible operations on the power spectrum. The log-polar transform is then used on the retained coefficients (Fig 2 c));
3. To the resulting log-polar image a second 2D Fourier transform is applied. The feature vector is constructed with a selected number of coefficients of the second magnitude spectrum using a binary mask with a special form – square 20 x 20 at each corner and first column at the left side of the image (Fig. 2 d) e));
4. A matrix with the feature vectors for all the face images of the database is constructed.

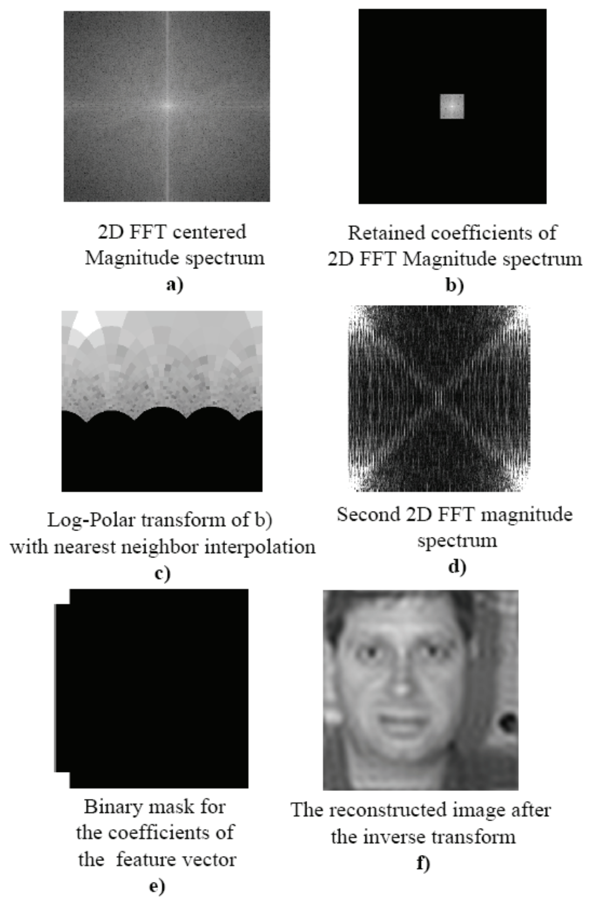


Fig. 2 Steps from 1 to 4 for the construction of the feature vector for the image from Fig. 1.

C. Face identification algorithm

The identification process represents nearest neighbourhood queries in high dimensional data space. The first step of the proposed algorithm for face identification is to calculate the Modified Euclidean Distance between each of the feature vectors in the database. It will allow a faster distance computation and combined with the modified angular distance, the whole computational time of the matching algorithm will be reduced.

The square Euclidean distance (D_E) between two vectors $\vec{X}$ and $\vec{Y}$, $\vec{X} = \{x_i, i = 1,...,N\}$ and $\vec{Y} = \{y_i, i = 1,...,N\}$, then D_E is represented as follows:

$$D_E(\vec{X},\vec{Y}) = \sum_{i=1}^{N} x_i^2 + \sum_{i=1}^{N} y_i^2 - 2\sum_{i=1}^{N} x_i y_i =$$

$$= \left\|\vec{X}\right\|^2 + \left\|\vec{Y}\right\|^2 - 2\sum_{i=1}^{N} x_i y_i \qquad (1)$$

To construct the modified square Euclidean Distance we consider two cases:

1. if $x_i \geq 0$ and $y_i \geq 0$ then

$$\sum_{i=1}^{N} x_i y_i \leq x_{\max} \sum_{i=1}^{N} y_i \qquad (2)$$

where $x_{\max} = \max\{x_i\}, i = 1,..., N$.

Then the modified distance is calculated as follows:

$$d_E(\vec{X},\vec{Y}) = \left\|\vec{X}\right\|^2 + \left\|\vec{Y}\right\|^2 - 2x_{\max} \sum_{i=1}^{N} y_i \qquad (3)$$

where $d_E(\vec{X},\vec{Y}) \leq D_E(\vec{X},\vec{Y})$.

2. if x_i and y_i are positive and negative then:

$$x_i' = x_i + |p| \qquad (4)$$

$$y_i' = y_i + |p| \qquad (5)$$

where $p = \min(x_1,..., x_N, y_1,..., y_N)$.

Then the modified distance is calculated:

$$d_E(\vec{X},\vec{Y}) = \left\|\vec{X}\right\|^2 + \left\|\vec{Y}\right\|^2 - 2x_{\max}' \sum_{i=1}^{N} y_i' \qquad (6)$$

For large vectors the computation of the square Euclidean distance is much faster because the number of multiplications and summations is reduced.

So after calculating the modified square Euclidean distance between each of the feature vectors in the database, we choose the 21 nearest neighbors to each face image. The second step of the algorithm is the calculation of the modified Cosine angle distance between these 21 neighbors. The Cosine angle distance (CAD) between two vectors $\vec{X}$ and $\vec{Y}$ is represented as follows:

$$D_\theta(\vec{X},\vec{Y}) = \arccos\left[\frac{\sum_{i=1}^{N} x_i y_i}{\left(\sum_{i=1}^{N} x_i^2\right)\left(\sum_{i=1}^{N} y_i^2\right)}\right] \qquad (7)$$

Using Eq. (2) we can rewrite the Eq. (7) as follows (modified CAD):

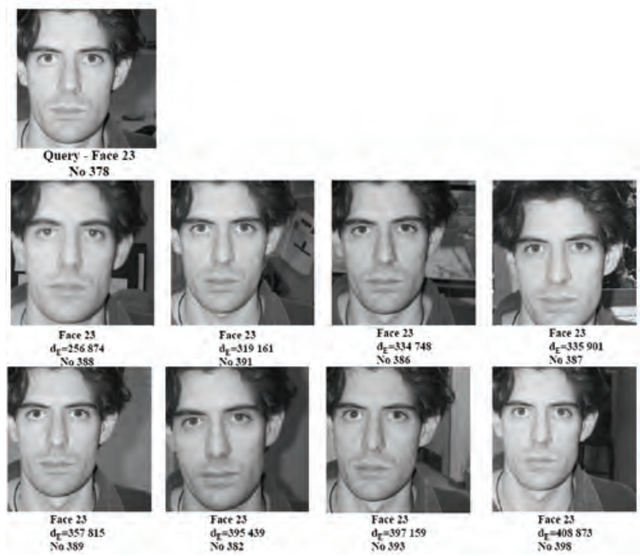
$$d_\theta(\vec{X},\vec{Y}) = \arccos\left[\frac{\sum_{i=1}^{N} y_i}{N x_{\max}\left(\sum_{i=1}^{N} y_i^2\right)}\right] \qquad (8)$$

One important property of CAD is that it gives a metric of similarity between two vectors unlike Manhattan distance and Euclidean distance, both of which give metrics of dissimilarities. Also $d_\theta \in [0,1]$. This makes it easy to combine distance between two images using multiple features. The normalization implied by the denominator in Eq. (8) prevents that two images having similar distributions of terms appear distant from each other just because one is much longer than the other. In fact, the cosine similarity seems to not outperform the conventional Euclidean distance when high dimensional spaces are concerned [8].

So we rearrange the 21 image feature vectors with modified CAD and with K-NN classifier where K= 9, we match the query face to the face witch is most frequently occurring in this neighborhood.

III. Experimental results

We apply the proposed identification algorithm on a face image database with 450 JPEG images with 31 faces with different lighting/expressions/backgrounds/ and male or female from the Computational Vision at the California Institute of Technology, USA. The number of face images is unevenly distributed. In the database 12 faces are present with 1, 5 or 7 images per face; the other 19 faces are present with around 20 images per face. The identification process will be performed only on these 19 faces; the others will be used in the search database. After the pre-processing in Section II the face images are with dimensions 256 x 256 pixels. After the Mellin-Fourier transform, each feature vector in has 1016 components. So the database for identification has 450 feature vectors with 1016 elements each. On Fig. 3 an identification result with a query image belonging to Face 23 with the square Euclidean distance is shown.



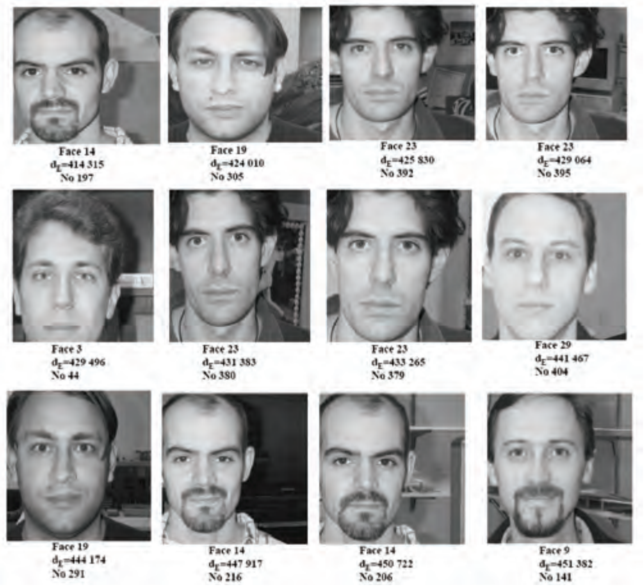


Fig. 3 Identification with a query image. The closest 20 images by square Euclidian distance are presented with their number in the database.

As mentioned in [8] the results with CAD are very similar to the results of the matching with the Euclidean distance. But the CAD is easier and faster to compute. The results of the identification for the 19 faces of the database are summarized in Table 1 – the confusion matrix after the classification with K-NN with K=9 using CAD. Only the diagonal with the rate of successful identification of the total confusion matrix is presented.

TABLE I
CONFUSION MATRIX –

Rate of successful identification in %	
Face 1	61.9%
Face 2	90%
Face 4	95.5%
Face 5	100%
Face 6	82.6%
Face 7	90%
Face 9	90.5%
Face 13	70%
Face 14	85.7%
Face 15	96%
Face 16	54.5%
Face 18	79%
Face 19	55%
Face 20	37.9%
Face 21	100%
Face 22	75%
Face 23	95.5%
Face 30	100%
Face 31	86.4%

IV. CONCLUSION

As shown on Table 1, the overall success rate of identification for all the faces is the database is 77.33%. Almost all of the faces are identified except the Face 20. For this face most the images were taken from far away and the face was not as visible as the others. The proposed method for the extraction of the feature vector of the face gives very accurate description of the characteristics of the particular face and with the very simple K-NN classifier we are able to identify each face in the database. The discrimination between female and male faces is excellent.

The method was developed in Matlab 7. Thanks to the modified Euclidean and Cosine angle distance, the search in all the database takes around 3 seconds on a standard PC configuration. The extraction of the feature vector takes around 2 seconds for each image.

The next step will be to test the algorithm on other databases not only with faces but with other objects. Also the method will be tested according to the FERET Evaluation Methodology [2]. This evaluation methodology is used by all the researchers to test the success rate for identification of faces of a given algorithm.

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