

IDENTIFICATION OF FACES BY MULTIMODAL INFORMATION FUSION OF DEPTH AND COLOR

¹ABDELMALIK Ouamane, ²MÉBARKA Belahcene, ³ABDELHAMID Benakcha, ⁴MOHAMED Boumehrez, ⁵ABDELMALIK Taleb Ahmed

^{1,2,4}LMSE Université Mohamed Khider Biskra Algérie, ¹ouamaneabdealmalik@yahoo.fr,

²belahcene_mebnaf@yahoo.fr, ⁴medboumehraz@netcourrier.com

³LGB Université Mohamed Khider Biskra Algérie, ^{benakcha_a@yahoo.fr}

⁵LAMIH Université de Valenciennes France, ^{abdelmalik.taleb-ahmed@univ-valenciennes.fr}

Abstract: Recognition of traditional optical faces of color images or intensity presents many challenges, such as variations in lighting, pose and expression. In fact, the human face not only generates 2D texture information, but also 3D shape information. In this paper, we examine what information the contributions of depth and color to make facial recognition when the variation in lighting and expression are taken into account. We present three methods of feature extraction based on reduction of one-dimensional space: the Linear Discriminant Analysis (LDA), Enhanced Fisher Linear Discriminant Model (EFM) and the Direct LDA (DLDA). A theoretical presentation of these approaches and their applications on the depth images and color is made. It is also a comparative study on information fusion of depth and color for both levels: characteristics and scores to select the most effective features and robust and thus build a strong classifier. The concatenation of feature vectors and fusion of the pixels of the image depth and color: the average, the product, the minimum and maximum are used in the case of fusion characteristics. For the merger to level scores, we used the fuzzy Sugeno integral and Choquet and support vector machines (SVM). The experiments are performed on the database CASIA 3D Face, complex data sets with variations, including variations in lighting, expression and longstanding failures between two scans. The experimental results show the promising performance of the proposed system. Note that in our system, all processes are performed automatically.

Keywords: depth images, color images, reduce space, fusion

1. Introduction

Recognition systems based on biometrics must be potentially effective to meet the needs of security, become an international concern. The face is a pretty interesting candidate for acquisition of non-contact and non-intrusive

nature for humans. Facial recognition is one of the areas of most active research in the study of pattern recognition and computer vision. Although 2D approaches have given good performance, they are very sensitive to the problems of changes in lighting conditions, pose, facial expressions and occlusions. To develop robust face recognition, additional information has been considered. Two solutions are: using infrared images [1] and use of 3D images [2, 3]. Infrared images are robust to changes in lighting environment, but they are too sensitive to temperature changes of the environment. Thus, their use is still limited. Another solution is to use the 3D information. With the development of 3D capturing equipment, it became easier and faster to obtain 3D shape and 2D texture information to represent a real face in 3D.

Face recognition from 3D information is not a new topic. Studies have been conducted since the end of last century [4, 5]. The 3D faces recognition, which can be classified into a method using point cloud representations of depth and representations of surface features of the face. Other surveys of the state of the art 3D face recognition can be found in [6, 7]. Recognition methods that work directly on 3D point clouds by considering the data in their original representation, based on spatial information and depth. A priori registration of point clouds is commonly performed by the iterative closest point (ICP) algorithm [8,9]. The classification is usually based on the Hausdorff distance to measure the similarity between the different point clouds [10]. Alternatively, recognition could be achieved with 3D eigenfaces which are built directly from 3D point clouds [11]. Another option is to extract geometric indices based on eigenvalues and singular values of the covariance matrix defined on the local neighborhood of each 3D point [12].

The main drawback recognition methods based on 3D point clouds, however, lies in their computational complexity which is driven by the large data size. Many

recognition systems use or depth images of the spectrum, where each pixel value represents the distance between the sensor and the surface of the face. 3D facial recognition is then formulated as a problem of size reduction of planar images. The principal component analysis (PCA) can be used to reduce dimensional. Recent methods have proposed to focus on cutting-dimensional facial landmarks such as the nose [13] or in multiple regions carefully chosen [14,15].

Alternatively, one could calculate the geodesic distances between points selected benchmarks [16]. However, these methods require a selection of reference points or areas of interest which is often done manually and prevents the implementation of fully automated systems.

All these studies illustrate the feasibility of 3D face recognition. However, due may be of limited data, the methods described above use only the shape characteristics of the facial surfaces, while ignoring the texture information.

3D facial recognition, combining the shape and intensity / color 2D in training, is a developing subject. The combination of 2D and 3D information provides an opportunity to improve the performance of face recognition. Wang et al. [17] described facial feature points by using Gabor filter responses in a 2D domain and point signatures in a 3D domain. Then, classification was done by support vector machines with a decision directed acyclic graph. Tsalakanidou et al. [18] constructed embedded hidden Markov models (EHMM) classifiers based on depth and intensity information and then used fusion rules to combine the matching scores. In [3], Chang et al. evaluated the recognition scheme with different combinations of 2D and 3D information and showed that the combination of 2D and 3D information was most effective in characterizing an individual.

The existing methods mentioned above, some problems remain distinct and outstanding:

- * Some studies [19, 3] were performed to compare the 2D and 3D face recognition. However, some details are ignored on how the depth and intensity information contributes to face recognition with an expression of lighting variations.
- * Only the decision level fusion is considered.

In this work, we try to solve these remaining problems in face recognition, and we examine how the depth information and color contributes to face recognition when the change in lighting and expression are taken into account.

The main contributions of this paper are:

- * Make a comparative study of methods for reducing data space as follows: Linear Discriminant Analysis (LDA), Enhanced Fisher Linear Discriminant Model (EFM) and the Direct LDA (DLDA) to select the best projection space data and color depth.

- * Study the characteristics level fusion.

- * Study the scores level fusion by: the fuzzy Sugeno integral and Choquet and support vector machines (SVMs).

2. Identification of faces 3D and 2D

Ideally, a facial recognition system must be able to identify faces in depth information or color. The basic operating principle of our face recognition system (Figure 1) can be summarized in three steps: preprocessing, space reduction and comparison.

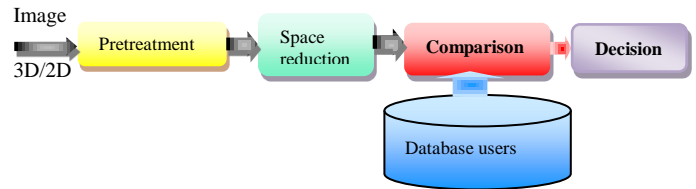


Fig. 1. Principle of operation of a system for 3D/2D face recognition

2.1. Pretreatment

It is assumed in this paper that one side is described by a 3D point cloud captured by a 3D laser scanner. Each point cloud consisting of thousands of points in 3D space. These discrete points describing the surface of the face. In our database CASIA 3D face every point is described with 3D spatial coordinates and the RGB color coordinates corresponding. In this section, we describe how the original data are preprocessed in 3D.

The data are converted into a 3D image depth (see figure. 2 (a)) and a color image (see figure. 3 (a)). In most images, the nose is the closest part of the face in 3D scanner; it has the highest value in depth between all points of the face. Using a window of size 3x3 which calculates the sum of the depth of its corresponding pixels, the nose is detected as the coordinates of the center pixel of the window that returns the maximum value (see figure. 2 (b)). After detecting the nose, all images in the database are cut by a rectangular window of size 57x47 centered around the center of the nose (see figure. 2 (c), figure. 3 (b)). For RGB color image, we used the HSV color space (Hue, Saturation, Value) (see figure. 3 (c)) and we consider the component V "Value" because it is less sensitive to lighting control (see figure. 3 (d)) [20]. However, because of the quality of the original data in 3D, the images of depth and color that we use usually contain a lot of noise, such as holes and outliers. We can obtain clear images by the following processes. The image preprocessing of the image and depth of the V component of the HSV color space includes noise suppression and the filling hole. For each pixel, the average is calculated by the sub-window size 5×5 around him. The result is shown in figures 2 (d), 3 (e).

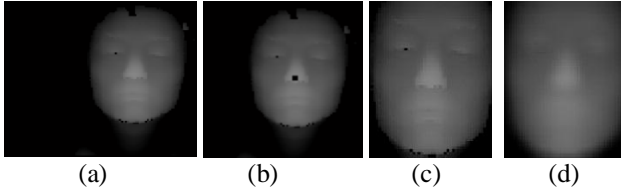


Fig. 2. Principle Pretreatment image depth: (a) the depth image, (b) detecting the nose tip, (c) Image cut (d) after removing the noise and filling holes

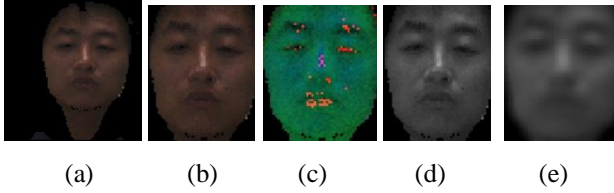


Fig.3. Pretreatment color image: (a) the color image, (b) Image cut, (c) Image HSV system, (d) The V component of HSV (e) by removing noise and filling holes

2.2. Methods to reduce space

A 2D image of the face is a signal two dimensions. It is the same for 3D face images because we converted the clouds of 3D points in 2D image depth. The number of points quickly becomes very large, even for small images. This dimensionality poses a number of problems for recognition algorithms, which are based on this representation of the image, namely:

- In a context of face recognition, working in a large space is a problem of computational complexity.
- For parametric methods, the number of parameters to estimate can quickly exceed the number of training samples, which penalizes the estimation.
- For non-parametric methods, the number of examples needed to effectively represent the distribution of data may be insufficient.

In 1994, Ruderman [21] has shown that natural images have a high statistical redundancy [3]. The advantage of the redundancy statistic is that it allows extraction of a simple structure of the important features and relevant image of the face. This structure would represent the face while keeping the most important information and therefore reduce the dimensionality of face space. The whole point of comprehensive approaches is the construction of the projection base that will compare, to recognize and analyze essential information of faces.

Linear Discriminant Analysis (LDA)

Principal Component Analysis (PCA) [22] is first used to project the images in a data space inferior. The purpose of LDA is to maximize inter-class distances while minimizing

the intra-class distances, which is to find the transformation matrix W that maximizes the criterion [22]:

$$J(W) = \frac{W^T S_b W}{W^T S_w W}$$

So W is ideal for:

$$W_{opt} = \underset{W}{\operatorname{argmax}} \left(\frac{|W^T S_b W|}{|W^T S_w W|} \right) = [w_1, w_2, \dots, w_m] \quad (1)$$

Let the training set containing L classes and each class X contains n_i samples. The intra-class matrices (S_w) and inter-class (S_b) are defined as:

$$S_w = \sum_{i=1}^L \sum_{\bar{x}_k \in X_i} (\bar{x}_k - \bar{m}_i) (\bar{x}_k - \bar{m}_i)^T \quad (2)$$

$$S_b = \sum_{i=1}^L n_i (\bar{m}_i - \bar{m}) (\bar{m}_i - \bar{m})^T \quad (3)$$

\bar{m} is the average of all the images for learning, \bar{m}_i is the average of the images in each class X_i and \bar{x}_k is the sample belonging to class X , the solution of problems in equation (3) is calculating the eigenvectors and eigenvalues.

$$S_b w = \lambda S_w w \quad (4)$$

W contains the eigenvectors by their associated eigenvalues in descending order. The LDA requires a large number of samples of all and creates a problem of over-adjustment to the training data and generalizes poorly to new data and testing. So the solution is the Enhanced Fisher Model [22].

Fisher Linear Discriminant Enhanced Model (EFM)

First, the Principal Component Analysis (PCA) [22] is used to project images in a data space inferior. Let the training set contain L classes and each class X_i contains n_i samples. The intra-class matrix (S_w) and inter-class matrix (S_b).

Whiten first S_w :

$$\Theta^{-1/2} \phi^T S_w \phi \Theta^{-1/2} = I, \quad (5)$$

Where, $\Theta \in \mathbf{R}^{m \times m}$ is the matrix of eigenvectors and the diagonal matrix of eigenvalues of S_w respectively. Second EFM proceeds to calculate the dispersion matrix inter-class K_b as follows:

$$K_b = \Theta^{-1/2} \phi^T S_b \phi \Theta^{-1/2} \quad (6)$$

Diagonalisons now the new dispersion matrix inter-class K_b :

$$K_b \Psi = \Psi \Lambda \quad (7)$$

Where $\Psi, \Lambda \in \mathbf{R}^{m \times m}$ is the matrix of eigenvectors and the diagonal matrix of eigenvalues of K_b respectively. The transformation matrix of the global EFM is defined as follows:

$$W = \phi \Theta^{-1/2} \Psi \quad (8)$$

The Direct LDA (DLDA)

A new approach, called the DLDA, was proposed in [23] to maximize the Fisher criterion. The first step in this

approach is the diagonalisation of the matrix S_b by calculating the matrix V :

$$V^T S_b V = \Lambda \quad (9)$$

With: $V^T V = I$. The problem is then reduced to solving an eigenvalue problem. Each vector of the matrix V is an eigenvector of the matrix S_b and Λ contains all the eigenvalues of S_b . As the S_b matrix can be singular, Λ may contain values of zero or very low. These values and the eigenvectors must be dismissed as a projection in the direction of these vectors provides no information discriminating between classes.

Let Y be the sub-matrix consisting of the first m columns of V (Y is of dimension $m \times n$ and n is the size of the input sample):

$$Y^T S_b Y = D_b > 0 \quad (10)$$

D_b with the sub-matrix of Λ of dimension $m \times m$.

Multiplying by $D_b^{-1/2T}$ and $D_b^{-1/2}$ of both sides we arrive at:

$$(Y D_b^{-1/2})^T S_b (Y D_b^{-1/2}) = D_b \quad (11)$$

By asking $Z = Y D_b^{-1/2}$, we obtain:

$$Z^T S_b Z = D_b \quad (12)$$

We note that Z reduces the size of $n \times m$ to S_b $m \times m$. Consider the diagonalization of the matrix $Z^T S_w Z$ by solving the eigenvalue problem:

$$U^T Z^T S_w Z U = D_w \quad (13)$$

with $U^T U = I$. D_w can contain null values on the diagonal. The objective is to minimize the dispersion of inter-class. It is therefore important to keep the projection vectors associated with the lowest eigenvalues, especially the zero values, and reject those associated with the largest eigenvalues. Posing the matrix $A = U^T Z^T$, A allows the diagonalization of the numerator and denominator of the Fisher criterion:

$$A S_w A^T = D_w \quad ; \quad A S_b A^T = I \quad (14)$$

Posing $\phi = D_w^{-1/2} A$, we obtain the projection matrix that meets the test of Fisher.

2.3. Comparison

Although the Euclidean distance is optimal in theory, various experiments have shown that the Euclidean distance is surpassed by other distances. One is the normalized correlation [24] which is defined by:

$$S(A, B) = \frac{A^T B}{\|A\| \|B\|} \quad (15)$$

This function simply calculates the cosine of the angle between two feature vectors A and B .

2.4. Results

The CASIA 3D database

We use the CASIA 3D Face database [25] to test our identification system proposed. The basis is constructed by a 3D scanner Minolta VIVID 910 non-contact working in the fast mode. This database contains 123 subjects, each subject having 37 or 38 images with individual variations of poses, expression, illumination, combined changes in expression under illumination and pose as expressions. This database contains complex variations that are difficult to any algorithm. In our work, we studied the variations of illumination (figure. 4), expressions (figure. 5) and the combined changes in expression under illumination. We therefore used 15 images for each subject. The database of 1845 images is divided into two sub-assemblies, all of the gallery and test set. The gallery set contains an image for each subject (under the condition of front view, office lighting and neutral expression). The test set is further divided into three subsets:

- IV (400 images): illumination variations, including top, bottom, left and right lighting.
- EV (500 images): expression variations, including smile, laugh, anger, surprise and eyes closed.
- EVI (500 images): expression variations under the lighting from the right side



Fig.4. Illumination variations of the CASIA 3D Face Database



(a) Smile (b) Laugh (c) anger (d) surprise (e) eye close

Fig.5. Expression variations of the CASIA 3D Face Database

Comparison of methods for reducing the depth images and color

In our experience, depth images and images of the V component of HSV color space are used to characterize the subjects. Figures 6 and 7 present the performance of

reduction methods for identification of depth images and color.

We can see in figure 6 and 7 that the PCA EFM method is better performance than the PCA + LDA followed by PCA + DLDA using a limited number of features in our CASIA 3D database of depth and color images. Table 1 donne the best results for the space reduction method PCA + EFM.

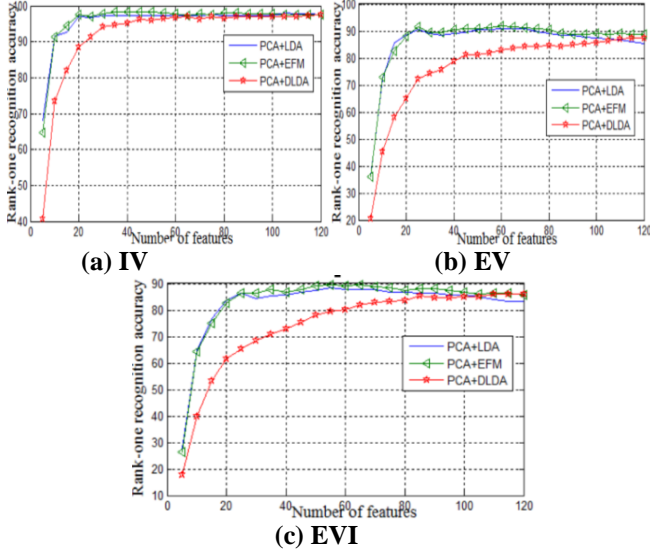


Fig. 6. Performance reduction methods for identification of depth images

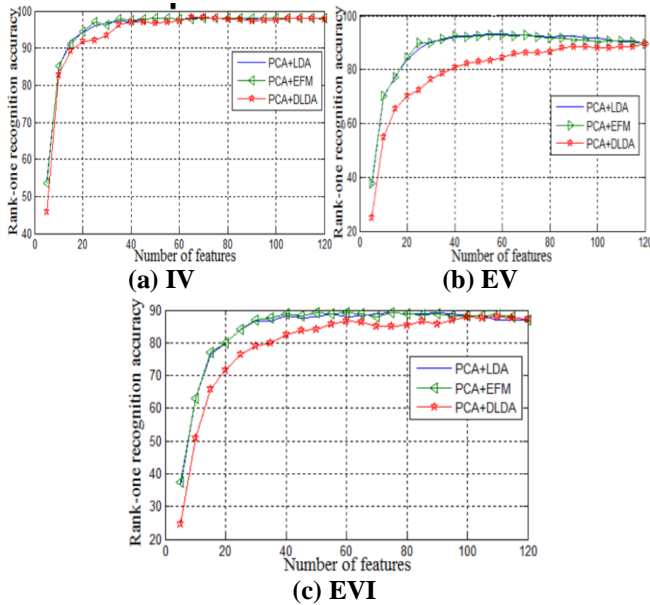


Fig.7. Performance reduction methods for identification of color images

Table 1

The best results for the space reduction method PCA + EFM.

Subsets of test	Depth images		Color images	
	Rank-one recognition accuracy	Number of features	Rank-one recognition accuracy	Number of features
IV	98.3740	35	98.1707	70
EV	92.0325	60	93.0081	55
EVI	89.5935	55	89.1057	60

The table shows that the depth information is almost equivalent to the color information, but the depth information is less sensitive to variation in illumination and color information is more efficient for variations in expression.

3. Multimodal fusion of depth and color

3.1. Feature level fusion

For feature level fusion we used two types:

- Merger by concatenating feature vectors for both depth and color.
- The merging of pixels in the image depth and color by: the average, the product, the minimum and maximum.

Figure 8 shows the performance of feature level for identification of faces.

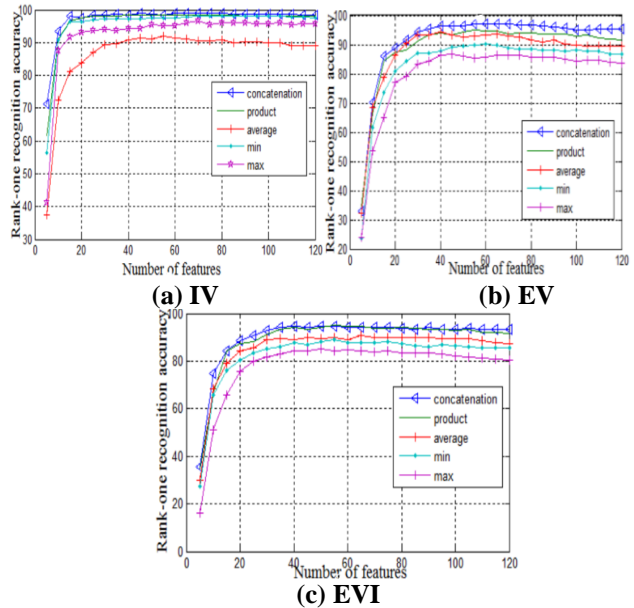


Fig.8. Performance of feature level for identification of faces

We noted in Figure 8 that the merger by the concatenation and the product gave almost the same

performance for the three test subsets. Table 2 presents the best results.

Table 2

The best results for the feature level fusion

subsets of test	Fusion method	Rank-one recognition accuracy	Number of features
IV	concatenation	98.9837	60
EV	concatenation	97.0732	60
EVI	product	94.9593	55

3.1. Score level fusion

The score level fusion is the kind of fusion most used because it can be applied to all types of systems (unlike the feature level fusion), in a dimensional space, with relatively simple methods and more effective, but dealing information that the merger decision. The merger of scores is therefore to the classification for the final decision.

There are two approaches to fusion of the scores obtained by different systems:

- The first approach is to treat the subject as a problem of combination,
- while the other approach is to see this as a classification problem.

For the first approach we used fuzzy logic based the Sugeno and Choquet integral. For the second approach we used a support vector machine (SVM).

The combination of the scores by the fuzzy logic

The theory of fuzzy logic (fuzzy subsets) was introduced by Zadeh in 1965 [26] as an extension of the logic on the one hand and an improvement valued logic, on the other. The importance of fuzzy logic is that it approaches the human reasoning through the integration and processing of approximate nature, vague, imprecise or vague human knowledge. Linguistic terms such as "approximately", "medium", "approximately" are likely to give vagueness to spoken sentences. The following algorithm shows how it's done by combining the two integrals [27]:

1. Calculating the fuzzy density function g^i

$$\begin{cases} g^i = \beta p_i, & i = 1 \\ g^i = (1 - \beta) p_i, & i = 2, 3, 4 \end{cases} \quad (16)$$

p_i is the classification rate in the interval $[0, 1]$ for each system. $B \in [0, 1]$ is a factor that establishes a balance between the results of the classification and i : the index of each system.

2. Calculation of λ by:

$$\lambda + 1 = \prod_{i=1}^n (1 + \lambda g^i) \quad (17)$$

where: $\lambda \in (-1, +\infty)$, $\lambda \neq 0$.

3. Calculation of $g(A_i)$ on the extent fuzzy subsets by:

$$g(A_i) = g(y_1) = g^1 \quad (18)$$

$$g(A_i) = g^i + g(A_{i-1}) + \lambda g^i g(A_{i-1}). \quad (19)$$

4. Calculation of the Sugeno fuzzy integral by:

$$\int_Y h(y) \circ g(\cdot) = \max_{i=1:n} [\min(h(y_i), g(A_i))] \quad (20)$$

$h(y_i)$ are the scores and are ranked in descending order, $n = 4$.

Or calculate the fuzzy Choquet integral by:

$$\int_Y h(y) d g(\cdot) = \sum_{i=1}^n [h(y_i) - h(y_{i+1})] g(A_i) h(y_{n+1}) = 0. \quad (21)$$

Classification scores with support vector machines (SVM)

The goal of SVM [28, 29] is to find a separator that minimizes the classification error on the training set. The SVM will also be performing generalization on data not used in learning. For this, the concept used is the margin (hence the name vector machines margin). The margin is the mean square distance between the separatrix and learning elements closest to it called support vectors in figure 9. These elements are called support vectors because it is only on those elements of the training set as the separatrix is optimized.

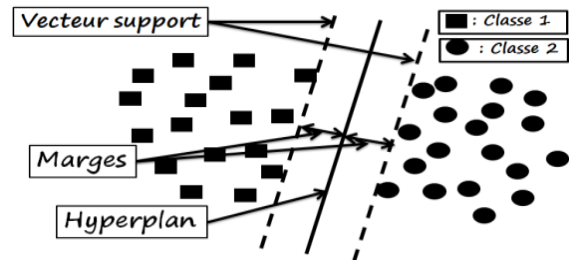


Fig.9. Linear separation in a two-dimensional space

Any classifier is to classify an element x in one of the possible classes. The label y with $y = -1$ and 1 , the classifier has to determine f such that:

$$y = f(x) \quad (22)$$

The SVM aims to find the best linear separator (in terms of maximum margin) in the space (transformed by the kernel function K , i.e. to determine the vector w and constant b such that the separatrix has to equation:

$$w \cdot k(x) + b = 0 \quad (23)$$

The distance between a point x_i in space and the hyperplane equation: $wk(x) + b = 0$ is equal to:

$$h(x_i) = \frac{w \cdot K(x_i) + b}{\|w\|} \quad (24)$$

To maximize the margin, should be minimized $\|w\|$ while maximizing $wk(x_i) + b$ for x_i defined as support vectors. These vectors are the media x_i for $i = 1$ to m of the training set such that $wk(x) + b = \pm 1$. Solving this optimization problem is done by using Lagrange multipliers is given by:

$$L(w, b, \alpha) = \frac{1}{2} \|w\|^2 - \sum_{i=1}^m \alpha_i (y_i (w \cdot K(x_i) + b) - 1) \quad (25)$$

with the coefficients α_i called Lagrange multipliers. To solve this optimization problem, we must minimize the Lagrangian with respect to w and b and maximized with respect to α . We use a support vector machine (SVM) with Radial Basis Function or RBF (see equation 23). The SVM was implemented using the freely available libsvm library site (<http://www.csie.ntu.edu.tw/~cjlin/libsvm/>). The RBF kernel used is of the form:

$$K_{RBF}(u, v) = e^{-\gamma \|u-v\|^2} \quad (26)$$

The SVM is a separator with two classes but in our problem we have 123 classes. We therefore used 123 SVMs.

Table 3 shows the performance of combination and classification depth and color image. To ensure that the merger of scores from different systems is consistent, scores must first be transformed into a common domain: this is called normalization of scores, the normalization method used donations our case is the method min-max given by:

$$s'_{ik} = \frac{s_{ik} - \min(\{s_i\})}{\max(\{s_i\}) - \min(\{s_i\})} \quad (27)$$

With: s_{ik} the k^{th} output score of the i^{th} SVM, $i = k = 1, 2, \dots, N$ (N is the number of subjects and also 123).

Table 3

Rank-one recognition accuracy for the combination and classification depth and color image.

Subsets of test	Fusion methods		
	Sugenointegral	Choquetintegral	SVMs
IV	98.98	98.98	100
EV	95.93	95.77	99.72
EVI	93.33	94.1463	99.18

Table 3 shows that the fusion combinations of scores for the two fuzzy integrals of Sugeno and Choquet gives results equivalent to those of the merger in terms of features, but the merger of scores by classification using SVMs gave results almost perfect. Our multimodal identification system faces is

thus insensitive to the variation in lighting and facial expression.

4. Conclusion

This document uses the depth and color images to build a robust classifier for face recognition. Since the dimensionality of the characteristics of depth and color images are very high, we studied three methods for reducing data space. Then we made comparative studies on information fusion of depth and color for both levels: feature and scores for the construction of an efficient classifier. By analyzing our experimental results in the database CASIA 3D face with complex variations, we illustrate the promising performance of the proposed scheme and draw the important conclusion:

- The best method for reducing space is PCA + EFM.
- The color information is more robust than the depth information on variations of expression; the depth information is more robust than intensity information under lighting variations.
- The fusion is useful in improving the recognition performance.
- The classification performance of SVMs outperforms scores by the merger in the feature and the combination of two scores by Sugeno and Choquet fuzzy integrals of.

In our work, we studied the variations of illuminations, expressions and expressions combined changes in illumination. But we did not study the individual variations of poses and lighting installation in expressions. For future work we propose to use Gabor filters on the information of depth and color and study other fusion strategies.

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