Improve Face Recognition Using Uncalibrated Photometric Stereo

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Abstract:

One characteristic of surface image is that the appearance of the surface which is a function of the illuminant direction as well as of the surface topography. Uncalibrated photometric stereo (UPS) is a method used for estimating the surface normal and the surface reflectance of images without a priori knowledge of the light-source direction or the light-source intensity. It is used for shape estimation, surface description and determines illumination direction with several kinds of applications and resources, mainly used for machine vision techniques.

In this paper a face recognition system using Uncalibrated Photometric Stereo technique was proposed. In this system a face image classified as either known or unknown depending on the surface features that extracted from an image using UPS. The system is trained with known faces images to classifying the newly coming test image into one of the classes is the main aspect of the classification system.

Many image databases with different types, poses, and illuminations were used. The measurement of the performance, the efficiency, and the robust of this system were presents. The experiments demonstrate that the proposed system gives high classification rate results, even when the lighting condition changes or when the images were noises. Also the face classification system using the UPS gives better results from the view of classification rates and execution times as compared with other techniques.

Keywords: Uncalibrated Photometric Stereo, Face Recognition, Classification System.

1. Introduction

The problem of face recognition has drawn considerable attention in the Computer Vision community. The concentrated effort of the research community in the last few years resulted in many novel approaches for image classification that improve the field quickly in a few years.

Classification of images is a crucial step in high-level image understanding. Extraction of semantics from visual data improves the efficiency of a wide range of applications like image clustering and retrieval [1].

The task of image recognition has a wide range of applications, including retrieval from image collections, iris recognition, pornography blocking and information extraction (IE). Selecting suitable variables is a critical step for successfully implementing image recognition. Many potential variables may be used in image recognition, including spectral signatures, vegetation indices, transformed images, textural or contextual information, multitemporal images, multisensor images, and ancillary data. It is important to select only the variables that are most useful for extracting features. Many approaches, such as principal component analysis (PCA), minimum noise fraction transform, discriminant analysis, decision boundary features extraction, non-parametric weighted features extraction, wavelet transform, spectral mixture analysis [2], multiwavelet transforms and 3D radon transform [3] may be used for features extraction, in order to reduce the data redundancy inherent in image data or to extract specific information.

The *"Photometric Stereo"* (PS) technique consists of obtaining several pictures of the same subject in different illumination conditions and extracting the 3D geometry by assuming the Lambertian reflection model [4]. The research efforts on the PS can be grouped into three directions: subspace methods, reflectance model methods, and 3D-model-based methods. (i) The first approach is very popular for the recognition problem. After removing the first three eigenvectors, principal component analysis (PCA) was reported to be more robust to illumination variation than the ordinary PCA or the 'Eigenface' approach [5, 6]. In general, subspace learning methods are able to capture the generic face space and thus to recognize new objects not present in the training set. The disadvantage is that subspace learning is actually tuned to the lighting conditions of the training set; therefore if the illumination conditions are not similar among the training, gallery, and probe sets, classification performance may not be acceptable. (ii) The second approach [7, 8] employs a Lambertian reflectance model with a varying albedo field; mostly ignoring both attached and cast shadows. The main disadvantage of this approach is the lack of generalization from known objects to unknown objects. (iii) The third approach employs 3D models. The 'Eigenhead' approach [9] assumes that the 3D geometry (or 3D depth information) of any image lies in a linear space spanned by the 3D geometry of the training ensemble and uses a constant albedo field. It is able to handle both illumination and pose variations

with illumination directions specified. The weakness of the 3D model approaches is that they require 3D models and complicated fitting algorithms.

"Uncalibrated Photometric Stereo" (UPS) or sometimes called Unconstrained Photometric stereo means that we do not have any priori knowledge of the light-source direction or the light-source intensity [10]. Changes in lighting can produce large variability in the appearance of images. Characterizing this variability is fundamental to understanding how to account for the effects of lighting in face recognition. UPS can be used for 3D shape recovery, illumination direction definition and surface description [11].

In this paper *"Uncalibrated Photometric Stereo*" technique, was used to extract surfaces normal and surfaces reflectance features of the face image such that mapping its data from the spatial domain to the frequency domain, to reduce the image data. Using simple statistical measures, these features then formulated as a features vector that are used to classify the test face image from the training classes in the face classification system.

The rest of this paper is organized as follows. Section 2, explained the background of the UPS algorithm, Section 3 explained the proposed face recognition system using UPS algorithm, Section 4 shows the experimental results. Finally the conclusions were in section 5.

2. UPS Background

The Photometric Stereo (PS) technique consists of obtaining several pictures of the same subject in different illumination conditions and extracting the 3D geometry by assuming the Lambertian reflection model. Changes in lighting can produce large variability in the appearance of images specialized the details such as faces, bodies…etc. An example of a face image, under three different lighting conditions shows in Fig (1) [9].

Fig.(1) The same face, under three different lighting conditions.

Photometric techniques use several images, imaged under different illumination conditions, with their own specific, reflectance map shown in Fig (2). Mathematically, this may be expressed as follows [10,11]: $i = n \cdot l$ …(1)

Where *i,* is the level intensity, *n, is* the unit surface normal, and *l,* is the unit light-source direction.

Unconstrained (Uncalibrated) Photometric Stereo (UPS) means that we do not have any priori knowledge of the light-source direction or the light-source intensity. However, in constrained Photometric Stereo the light-source direction is not unknown, and for this reason will be easier to determine the surface normal and the surface reflectance.

In this method, assuming only that the object's surface is Lambertian, the surface normal, and the surface reflectance, the light-source direction, and the light-source intensity can be determined simultaneously which, can be estimated from intensity images that are obtained under a light-source arbitrarily moved by a human. This method does not rely on any smoothness assumptions for these parameters [9].Assuming that the object's surface is Lambertian, which is a surface with perfectly matte properties, which means that these surfaces reflect light with equal intensity in all directions, and hence appear equally bright from all directions. For a given surface, the brightness depends only on the angle θ between the direction of the lightsource *L* and the surface normal *N* Fig. (2) [10].

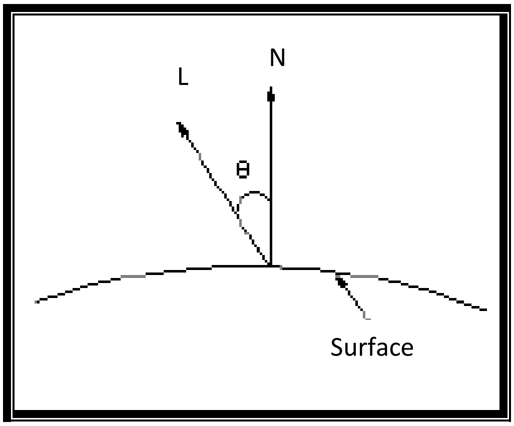

Fig (2): Lambertian Reflection

The image data matrix *I* can be factorized into surface matrix *S* and light-source matrix *L* follows [10,11]:

- **First of all, define the image data matrix *I*. Assuming that we measure the image intensity data *i* at *p* pixels through *f* frames by moving only a light-source. The image intensity data *i* is arranged as a $p \times f$ matrix *I* , with 1 row/pixel and 1 column/frame:**

$$I = \begin{bmatrix} i_{11} & \cdots & i_{1f} \\ \vdots & \cdots & \vdots \\ i_{p1} & \cdots & i_{pf} \end{bmatrix} \qquad \ldots(2)$$

- **Compute the (Singular Value Decomposition) SVD, (SVD is a widely used technique to decompose a matrix into several component matrices, exposing many of the useful and interesting properties of the original matrix) of the image data matrix, assuming that $p \geq f$, the matrix can be decomposed into a $p \times f$ matrix U, a diagonal $f \times f$ matrix $\sum$, and an $f \times f$ matrix V:** $I = U \sum V$ **...(3)**

where $U^T U = V^T V = V V^T = E$, and E is the $f \times f$ identity matrix.

$\sum$ is a nonnegative diagonal matrix whose diagonal entries are the singular values $\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_f \geq 0$ sorted in nonincreasing order.

This is the *SVD* of the matrix *I*. when you focus only on the first three columns of *U*, the first 3×3 submatrix of $\sum$, and the first three rows of *V*, then these matrices can be partitioned as follows:

$$. \; U = \begin{bmatrix} \underbrace{U'}_{3} & \underbrace{U''}_{f-3} \end{bmatrix} \} \, p \qquad \text{...(4)}$$

$$. \; \Sigma = \begin{bmatrix} \Sigma' & \mathbf{0} \\ \underbrace{\mathbf{0}}_{3} & \underbrace{\Sigma''}_{f-3} \end{bmatrix} \begin{matrix} \}\,3 \\ \}\,3 \end{matrix} \qquad \text{...(5)}$$

$$V = \begin{bmatrix} V' \\ \underbrace{V''}_{f} \end{bmatrix} \begin{matrix} \}\,3 \\ \}\,3 \end{matrix} \qquad \text{...(6)}$$

- **Define the pseudo surface matrix $\hat{S}$ and the pseudo light-source matrix $\hat{L}$ as:**

$$\hat{S} = U' \left(\pm [\Sigma']^{1/2} \right) \qquad \text{...(7)}$$

$$\hat{L} = \left(\pm [\Sigma']^{1/2} \right) V' \qquad \text{...(8)}$$

There are two different signs for the pseudo solutions. They correspond to the solutions in the right-handed and the left-handed coordinate systems.

- **. Due to the pseudo surfaces matrices $\hat{S}$ and $\hat{L}$ being different from *S* and *L* in general, the matrix *A* must be found such that**

$$S = \hat{S} A \qquad \text{...(9)}$$

$$L = A^{-1}\hat{L} \qquad \text{...(10)}$$

But, this matrix is impossible to find without any knowledge of the surface and light characteristics. Then, the following useful constraint is used:

- Find at least 6 pixels in which the relative value of the surface reflectance is constant or known.

To find the matrix *A* using this constraint, first of all, extract $p'(\geq 6)$ pseudo surface vectors *s*ˆ of matrix $\hat{S}$ knowing that:

$$\hat{s}_k^T \; AA^T \; \hat{s}_k = 1, \qquad \text{...(11)}$$

where* k = 1, ... , *p

Then, introduce the symmetric matrix $B = AA^T$, rewrite (11) as:

$$\hat{s}_k^T \; B \; \hat{s}_k = 1, \qquad \text{...(12)}$$

Therefore:

$$\underbrace{[abcefi]}_{B}\underbrace{\begin{bmatrix} x^2 & & x^2 \\ 2xy & & 2xy \\ 2xz & & 2xz \\ & \cdots\cdots\cdots & \\ y^2 & & y^2 \\ 2yz & & 2yz \\ z^2 & & z^2 \end{bmatrix}}_{k} = \underbrace{[1\cdots\cdots 1]}_{k} \qquad \text{...(13)}$$

Once *B* is determined, the matrix *A* takes the *SVD* of *B*. $B = W\prod W^T$, where *W* is diagonal and $\prod$ is orthonormal. Then, let $A = W[\prod]^{1/2}$.

- Compute the surface matrix *S* and light-source matrix *L* as:

$$S = \hat{S}\,A \qquad \text{...(14)}$$

$$L = A^{-1}\hat{L} \qquad \text{...(15)}$$

The surface matrix *S* and light-source matrix *L* are in an arbitrary 3D coordinate system. These matrices can be aligned to the viewer-oriented coordinate system by solution of an absolute orientation problem [11].

- First of all, let the coordinates of the three points in each of the two coordinates system be $r_{l,1}$, $r_{l,2}$, $r_{l,3}$ and $r_{r,1}$, $r_{r,2}$, $r_{r,3}$, respectively.

- Construct: $x_l = r_{l,2} - r_{l,1}$ ...(16)
- Then $\hat{x}_l = x_l / \|x_l\|$ ...(17)

is a unit vector in the direction of the new x axis in the left-hand system.

- Now let $y_l = (r_{l,3} - r_{l,1}) - \left[(r_{l,3} - r_{l,1}) \cdot \hat{x}_l\right] \hat{x}_l$ ...(18)

  the component of $(r_{l,3} - r_{l,1})$ perpendicular to $\hat{x}$. The unit vector $\hat{y}_l = y_l / \|y_l\|$ is in the direction of the new y axis in the left-hand system.

- Use the cross product find $\hat{z}$

  $\hat{z} = \hat{x}_l \times \hat{y}_l$ ...(19)

This construction is now repeated in the right-hand system to obtain $\hat{x}_r$, $\hat{y}_r$ and $\hat{z}_r$.

- Now adjoin column vectors to form the matrices M_l and M_r as follows:

  $M_l = |\hat{x}_l\ \hat{y}_l\ \hat{z}_l|$, $M_r = |\hat{x}_r\ \hat{y}_r\ \hat{z}_r|$ ...(20)

The rotation matrix is given by

$$R = M_r M_l^T \qquad \text{...(21)}$$

- Finally, the surface matrix S and light-source matrix L in an absolute coordinate system are

$$L = L^T R \qquad \text{...(22)}$$

$$S = S^T R \qquad \text{...(23)}$$

The standard Lambertian equation does not handle shadows or specular reflections, which occur naturally in face images. The augmented model is then:

$$i(x) = n(x)^T s + e \qquad \text{...(24)}$$

which says that at pixel position x , the pixel intensity, $i \in R$, is related to dot product of the surface normal (including albedo) at that pixel, $n \in R^3$, and the single light source, $s \in R^3$, plus an error term $e \in R$. The purpose of this error term is to model shadows and specular reflections, without explicitly recovering the full 3D shape (depth) of the face. More precisely, let B be a $d \times m$ matrix whose columns are the d-dimensional images taken under illumination directions $\{s_j\}_{j=1}^{m}$. Let ***N*** be a $3\times d$ matrix whose columns are the vectors $\{n(x)\}_{x=1}^{d}$. Also, let ***S*** be a $3\times m$ matrix of the illumination directions, and let ***E*** be a $d\times m$ matrix of the error terms. Then for each person in the bootstrap set, compute the least-squares solution for ***N*** and ***E*** as follows[11]:

$$\begin{aligned} & B = N^T S + E \\ \Rightarrow\quad & N = (S S^T)^{-1} S B^T \\ and\quad & E = B - N^T S \end{aligned} \qquad \text{...(25)}$$

Fig (3) shows an example of face surface constructed using UPS algorithm. And Fig (4) shows the nine constructed images for face image using UPS algorithm (first three images are the *E* component matrix, second three images are the *B* component matrix, and the third are the *S* component matrix).

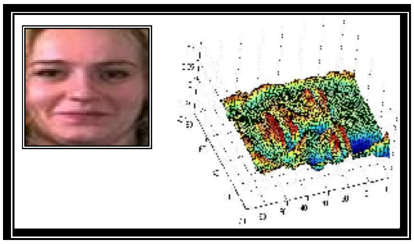

Fig (3) Constructed face surface using the UPS algorithm

Fig (4) the original image with nine construction images using UPS (the 1st three images are the E component, the 2nd three images are the B component, and the 3rd three images are the S component matrix)

3. System Measurements

The problem of reducing the representation of an image to a small number of components carrying enough discriminating information is referred to as "*features extraction*". An efficient way of reducing dimensionality and characterizing the image information is to compute a set of *"moments"*, such as *"mean".* For the *x(i, j),* where (*i=1,…,M, j=1,…,N*) a features extracted matrix it can find the features vector using the following equation [12]:

$$mean = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} |x(i,\ j)| \qquad ...(26)$$

"Correlation" is one of the similarity measurements, which is a measure of the association strength of the relationship between two variables. The greater the correlation between the testing image features vector and the training image features vector the greater the similarity, so the greater matching. Given the test image features vector representation *A*, and a training image features vector representation *B*, then the correlation measurement $\rho(A,B)$ between two vectors *A* and *B* is defined by [13]:

$$\rho(A,B) = \frac{<A,B>}{\sqrt{<A,A><B,B>}} \qquad ...(27)$$

Where the < *A, B* > is the dot product between *A* and *B,* the similarity ρ will return a value between -1 and 1. If $\rho(A,B)$ =1, then *A* and *B* are perfectly matched, while $\rho(A,B)$ =-1 mean *A* and *B* are perfectly unmatched.

To evaluate the performance of the proposed system, the classification rate can be calculated as [12]:

$$Classification\ Rate = \frac{Number\ of\ correctly\ classified\ patterns}{Total\ number\ of\ patterns} \times 100\ \% \qquad ...(28)$$

4. The Proposed Recognition System using UPS

An automatic classification system is proposed to recognize a face image input to the system as known or unknown person. The databases used in this system are the three database sets which consist of images varied in expressions, illuminations and poses. The user must select the database after loading the image to be recognized. The UPS algorithm was proposed as a features extraction method which provides a specific face image features even it varied in expressions, illuminations and poses. Then the features vector of the unknown image can be classified as known or unknown with the features vectors of the database using the correlation measurement. If the face image is misclassified then it can be stored as a new individual in the database. The block diagram of this system is displayed in Fig (5).

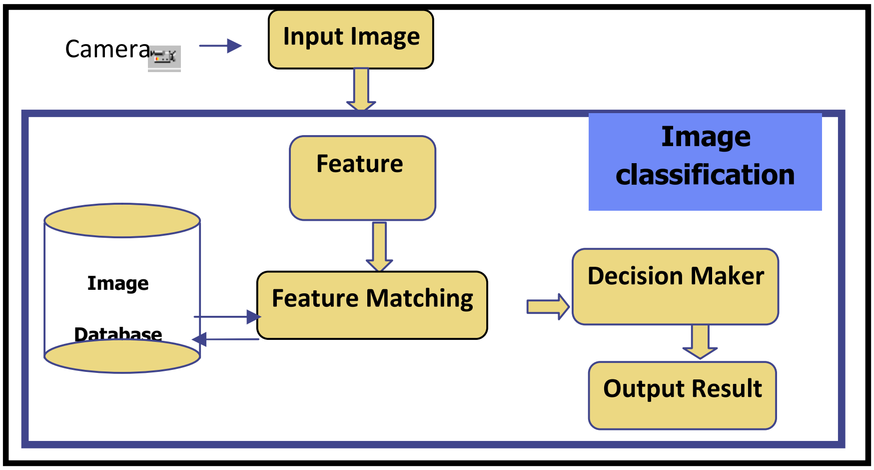

Fig (5) Classification system phases

4.1 System Databases

Any automatic classification system need a database, therefore three databases were constructed. The first database is a standard Dr. Libor Spacek face database [14]. This database has four sets of faces images, which are 24 bit RGB, of (JPEG) format taken under different lighting conditions, varied in expression, illumination, skin color, background, ages, and faces shapes (the mouth and eyes are open or closed, with or without glasses, male and female... etc). Two sets were selected from this database: the first set named *expressions database*, which consist of 30 frontal individuals of 6 images per each individual (i.e. 180 face images), varied in expression, skin color, ages, and shapes. The second set named *illuminated database*, which consist of 20 frontal individuals of 6 images per each individual (i.e. 120 face images) varied in illumination, expression, skin color, ages, and shapes. Some of these images show in fig (6). The second database named *Multi-image Database* (MDB) was constructed from 45 images differentiated in format (JPEG, BMP), and in contained, some of these images shown in fig (7). The third database is the Computer Vision Laboratory (CVL) database from University of Ljubljana [15]. All face images in this database are 24 bit RGB, of (JPEG) format taken with Sony Digital camera under uniform illumination. From this database 29 individuals with 6 images per each individual (i.e. 174 face images) were selected to construct a data set named *pose database* set with three pose classes: full profile, half profile (pose), and frontal as shown in Fig (8).For each pose class, there are only two images. According to the three pose this data set can be splited into three sets: pose, profile, and frontal, each set have 58 individuals with two images.

Fig (6) Samples of Dr. Libor Spacek face database.

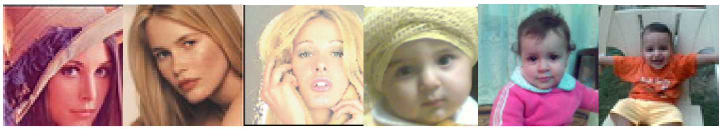

Fig (7) Samples of (MDB) database.

Fig (8): Samples of CVL face database (Pose database)

4.2 The Features Extraction

The UPS algorithm was used as a features extraction technique in the proposed recognition system. First of all the colored images are separated into their RGB bands then a 3D matrix is constructed from all the three bands of all the images of each face image class in the database or all the three band of the test face image. Then the UPS is used to extract the features matrices *S, B*, and *E* (equations 25).

For the purpose of dimension reduction of the features matrices (*S, B, and E*), the following features vector equation is proposed:

$$V_f = V_B \cup V_S \cup V_E \qquad ..(29)$$

Where V_B is the features vector of matrix *B*, V_S is the features vector of matrix *S*, and V_E is the features vector of matrix *E*. An example of the implementing UPS algorithm and features vector extraction of a face image displayed in fig (9).

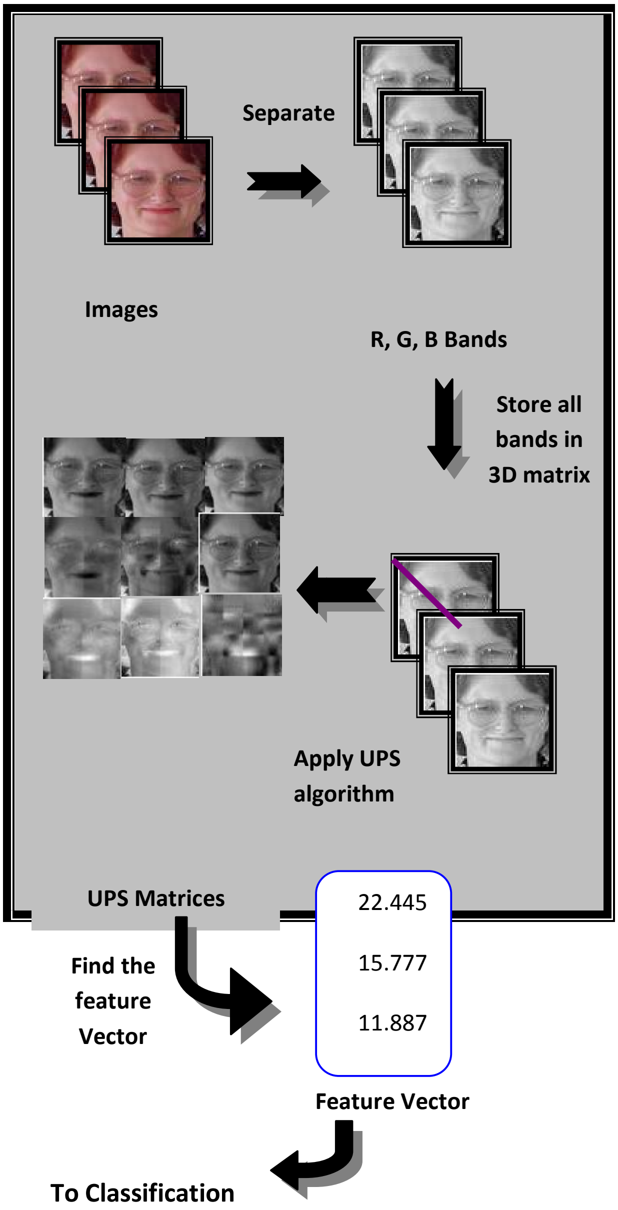

Fig. (9) An example of implementing UPS algorithm and features vector extraction on face images.

Briefly after loading the test image and selecting the desired database the following steps are applied to implement face image classification using Uncalibrated Photometric Stereo algorithm:

Step 1: Separate the three colored bands for all the images in each training class.

Step 2: Construct a 3D matrix from all the color bands for all images.

Step 3: Extract the features matrices *S*, *B*, and *E* by Implementing the UPS algorithm on the 3D matrix.

Step 4: Find the final features vector using the mean equation from the features vector $V_f = V_B \cup V_S \cup V_E$ of the vectors of *S*, *B*, and *E* matrices.

Step 5: Repeat steps (1- 4) for all the training classes and the test image.

Step 6: Classify the test image by calculate the correlation between the mean vector for each class in the database and the features vector for the test image (the greater the correlation the best match).

5. Experimental Results

Implementing classification system for face recognition using UPS algorithm gives excellent classification rates 100% for the MDB, (99.16% and 98.88% respectively) for the two selected training sets from the Spacek databases (the first is faces with different expressions and the second set is faces with different illuminated) and very good rate 82.183% for CVL database as shown in fig (10). These results due to the UPS technique which gives good features of face image even there are changes in light, shape, size, and even without any priory knowledge of light source.

The UPS algorithm takes a reasonably low execution time even when it's applied on different types and sizes of images. The result of this experiment shown in table (1), from this table it can be seen that the UPS algorithm is simple and efficient to execute.

Other techniques such as 3D radons transform, Multiwavelet transform and PCA techniques can be applied as features extraction techniques for face recognition. A comparison experiments between the UPS and these techniques from the view of the execution time (in seconds) can be shown in table (2). It is clear that the UPS algorithm is the faster for different types and sizes of images, this is due to the simplicity of UPS algorithm over the other methods. Table (3) shows a comparison among these techniques from the view of classification rates. It can be seen that the proposed system gives the best classification results for all types of databases over the other techniques.

All images in the databases used in this system were captured from the internet; they are not pure images and should contain a percent of noise. The robust of the UPS algorithm can be checked by adding more noise to the tested image before classify it. Therefore a Gaussian noise with zero mean and variance = 0.01 was added. Fig (11) shows the classification rates results after adding a Gaussian noise to the images. From this figure it is clear that the system using UPS algorithm is not affected by adding the noise. The classification rates still high and the error rates still low.

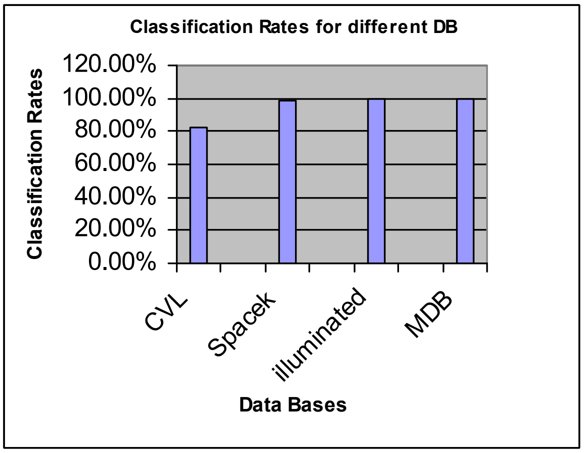

Fig (10) Classification Rates for applying UPS algorithm on different databases

Table (1) Execution time for UPS algorithm applied on different types and sizes of images

IMAGE (SIZE)	*TIME (SECOND)*
Nimr.jpg (64×64)	0. 1875
10.jpg (64×64)	0. 0625
Helda..jpg (64×64)	0. 1719
Spine.jpg (128×128)	0. 2188
Boat.bmp (128×128)	0. 1406
Flow.bmp (256×256)	0. 3438
Peppers.jpg(512×512)	1. 0469
Butty.bmp (512×512)	1. 0156

Table (2) Comparison of execution time (seconds) results between the UPS and the other techniques.

IMAGE (SIZE)	*PCA TIME*	*MULTIWAVLELET TIME*	*3D RADON TIME*	*UPS TIME*
Nimr.jpg (64×64)	0. 4060	0. 2656	1. 8281	0. 1875
10.jpg (64×64)	0. 2406	0. 2666	1. 8906	0. 0625
Helda..jpg (64×64)	0. 2344	0. 2500	1. 8281	0. 1719
Spine.jpg (128×128)	0. 5625	0. 9688	2. 6563	0. 2188
Boat.bmp (128×128)	0. 6500	0. 6250	2. 9531	0. 1406
Flow.bmp (256×256)	0.7813	6. 5313	3. 9375	0. 3438
Peppers.jpg(512×512)	1. 3125	52. 2188	10. 2188	1. 0469
Butty.bmp (512×512)	1. 0781	59. 9219	10. 1094	1. 0156
AVARAGE	0. 6081	15. 131	4. 4277	0. 3984

Table (3) Comparison of classification rate results between the UPS and the other

Transformation Techniques	Classification rates for Spacek (expressions) database	Classification rates for Spacek (illuminated) database	Classification rates for CVL	Classification rates for MDB
PCA	96.111%	96.666%	72.988%	99%
Multiwavelet	92.5%	92.5%	80.45%	98%
3D Radon	96.111%	97.5%	82.08%	98%
UPS	98.888%	99.160%	82.183%	100%

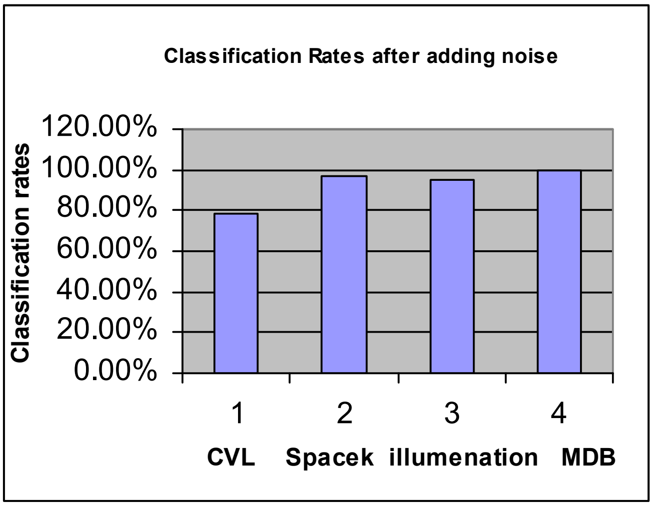

Fig (11) Classification rates after adding a noise for different databases

6. Conclusions

An automatic classification system for face recognition using the UPS algorithm is proposed. It is possible to find a general method to classify images depending on average measure which can be extracted from the features of the images. Very simple statistical features such as the mean provide good measure basis for image classification using the correlation metric which is an efficient metric to classify and identify person.

The Uncalibrated Photometric Stereo technique was proposed to use as a features extraction technique for the face recognition system, which gives an excellent classification rates for different databases taken under different lighting conditions, varied in expression, illumination, background, and faces shapes with a reasonability low execution time. The UPS technique is excellent technique because for extracting features of face image even its changes in lighting, shape, size, or even its without any priory Knowledge of light source.

The efficiency of the UPS algorithm is better in compare to with other algorithms such as PCA, Multiwavelet transform, and 3D radon transform, this is due to the simplicity of the UPS algorithm over the other algorithms, such that it takes execution time lower than the other algorithms as an average range between 0.2097 - 14.7326 seconds.

Also the proposed system using UPS algorithm gives better classification rates for all types of databases as compared with the other techniques. This means that the features extracted by using the UPS algorithm (surface properties) are more accurate than the other methods.

Finally the proposed system using UPS algorithm is robust in case of adding noise to the images. The classification rates are still high after noise is added to the test image and also the error rates still low.

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تحسين تمييز الوجه باستخدام التصوير المجسم غير محدد الإضاءة

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المستخلص:

واحدة من خصائص سطح الصورة هو ظهور السطح كدالة لاتجاه الإضاءة وكذلك كدالة لتكوين السطح. التصوير المجسم غير المحدد بالإضاءة يستخدم كطريقة لتخمين طبيعة السطح وانعكاس السطح للصور بدون علم مسبق عن اتجاه مصدر الضوء أو كثافة مصدر الضوء.وهويستخدم كطريقة لتخمين الشكل، وصف السطح وتحديد اتجاه الإضاءةِ مع عِدّة أنواع من التطبيقاتِ والمصادر، وبشكل رئيسي لتقنياتِ رؤيةِ الماكنةِ.

في هذا البحث تم اقتراح نظام تمييز الوجه باستخدام UPS ؛ في هذا النظام صورة الوجه اما "تعرف" او "لا تعرف " اعتمادا على خصائص السطح التي يتم استخلاصها من الصورة باستخدام خوارزمية UPS. تم يتم تدريب النظام بصوروجوه معروفة ويقوم النظام بتصنيف الصورة المراد اختبارها باحدى الاصناف الرئيسية المحددة.

عدة قواعد بيانات صورية تم استخدامها بأنواع متعددة ، وقفات واضاءات مختلفة. انجاز، كفاءة وقوة هذه الخوارزمية تم قياسها. التجارب وضحت إن النظام المقترح أعطى نتائج بنسب تصنيف عالية حتى عند تغيير شرط الإضاءة أو تشويه الصور. كذلك فان نظام تصنيف الوجه باستخدام التصوير المجسم غير محدد الإضاءة أعطى نتائج أفضل من ناحية نسبة التصنيف وزمن التنفيذ مقارنة بتقنيات أخرى.