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Face Identification

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Abstract:
Facial Identification is a type of biometric software application that can identify a specific individual in a digital image by analyzing and comparing patterns. Facial identification systems are commonly used for security purposes but are increasingly being used in a variety of other applications. Current two-dimensional face identification approaches can obtain a good performance only under constrained environments. This paper proposes a novel facial feature extraction method named Gabor Wavelets, PCA and SVM, which integrates the distinctiveness of Gabor features although the Gabor representations were largely used, particularly in the algorithms based on global approaches, the Gabor phase was never exploited, followed by a face recognition algorithm, based on the principal component Analysis approach and Support Vector Machine (SVM) is used as a new classifier for pattern recognition.The problems that arise in face identification are mainly of four types 1. Illumination 2.Occlusion 3. Aging 4. Facial expression and orientation. Based on our research we found best methods to handle illumination, Poses, and expression.

Index terms: Face Recognition, Feature Extraction, Gabor Features, PCA, SVM

I. INTRODUCTION

Face detection involves separating image windows into two classes; one containing faces (targets), and one containing the background (clutter). Our focus is on image-based face recognition. Given a picture taken from a digital camera, we'd like to know if there is any person inside, where his/her face locates at, and who he/she is. Towards this goal, we generally separate the face identification procedure into three steps: Face Detection, Feature Extraction, and Face Recognition**.**

Face Detection:
The main function of this step is to determine (1) whether human faces appear in a given image, and (2) where these faces are located at. The expected outputs of this step are patches containing each face in the input image. In order to make further face recognition system more robust and easy to design, face alignment are per-formed to justify the scales and orientations of these patches. Besides serving as the pre-processing for face recognition, face detection could be used for region-of-interest detection, retargeting, video and image classification, etc.

Feature Extraction:
After the face detection step, human-face patches are extracted from images. Directly using these patches for face recognition have some disadvantages, first, each patch usually contains over 1000 pixels, which are too large to build a robust recognition system1. Second, face patches may be taken from different camera alignments, with different face expressions, illuminations, and may suffer from occlusion and clutter. To overcome these drawbacks, feature extractions are performed to do in-formation packing, dimension reduction, salience extraction, and noise cleaning. After this step, a face patch is usually transformed into a vector with fixed dimension or a set of fiducially points and their corresponding locations. We will talk more de-tailed about this step in Section 2. In some literatures, feature extraction is either included in face detection or face recognition.

Face Recognition:
After formulizing the representation of each face, the last step is to recognize the identities of these faces. In order to achieve automatic recognition, a face database is required to build. For each person, several images are taken and their features are extracted and stored in the database. Then when an input face image comes in, we perform face detection and feature extraction, and compare its feature to each face class stored in the database. There have been many researches and algorithms pro-posed to deal with this classification problem, and we'll discuss them in later sections. There are two general applications of face recognition, one is called identification and another one is called verification. Face identification means given a face image, we want the system to tell who he / she is or the most probable identification; while in face verification, given a face image and a guess of the identification, we want the system to tell true or false about the guess.

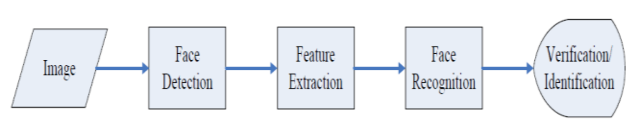

Figure.1. Configuration of a general face recognition Structure [ ].

Although significant improvement on performance has been achieved recently in this field, it is still a challenging task for real life environments due to the large intra-class facial variations, such as pose, illumination, expression, aging and the small interclass differences [2]. Feature extraction is one of the most important steps in the process of face recognition in order to overcome these problems.

The main approaches used for face feature extraction are usually grouped into two categories [3], namely holistic subspace analysis and local feature description. Gabor functions provide the optimal resolution in both the time (spatial) and frequency domains, and the Gabor wavelet transform seems to be the optimal basis to extract local features for several reasons [1]:

- ***Biological motivation:***

The simple cells of the visual cortex of mammalian brains are best modeled as a family of self-similar 2D Gabor wavelets.

- ***Mathematical and empirical motivation:***

Gabor wavelet transform has both the multi-resolution and multi-orientation properties and are optimal for measuring local spatial frequencies. Besides, it has been found to yield distortion tolerance space for pattern recognition tasks. Based on these advantages of Gabor wavelet transform, it has been used in many image analysis applications, and this report focus it's applications on face recognition, texture classification, facial expression classification, and some other excellent researches. Two representative methods of local feature analysis in face biometrics are Gabor wavelets [2] and Local Binary Patterns (LBP). Gabor wavelets can extract the local features of facial regions on multiple channels of frequencies and orientations. Both magnitude and phase information of Gabor wavelets can be used for face recognition. A typical example of Gabor phase features for face recognition is the Histogram of Gabor Phase Patterns (HGPP) [1]. HGPP can achieve a good performance, but the size of its feature template is 90 times that of a face image. In general, a common shortcoming of Gabor wavelets is the high dimensionality of feature vectors. Two representative methods of local feature analysis in face biometrics are Gabor wavelets [3] and Local Binary patterns (LBP) [4]. Gabor wavelets can extract the local features of facial regions on multiple channels of frequencies and orientations. Both magnitude and phase information of gabor wavelets can be used for face recognition. For example, the success of LBP comes from the robust binary encoding between the central pixel and its neighboring pixels. It is invariant to any monotonic transformation of intensity values for all image pixels in a local face region.

2. RELATED WORK

GABOR WAVELET TRANSFORM

The Fourier transform has been the most commonly used tool for analysing frequency properties of a given signal, while after transformation, the information about time is lost and it's hard to tell where a certain frequency occurs. To solve this problem, we can use kinds of time-frequency analysis techniques learned from the course [3] to represent a 1-D signal in time and frequency simultaneously. There is always uncertainty between the time and the frequency resolution of the window function used in this analysis since it is well know that when the time duration get larger, the bandwidth becomes smaller. Several ways have been proposed to find the uncertainty bound, and the most common one is the multiple of the standard deviations on time and frequency domain:

$$\sigma t^2 = \frac{\int t^2 |x(t)|^2 dt}{\int |x(t)|^2 dt}, \sigma_t^2 = \frac{\int f^2 |x(f)|^2 df}{\int |x(f)|^2 df} \qquad (1)$$

$$\sigma t \times \sigma f \geq \frac{1}{4\pi} \qquad (2)$$

Among all kinds of window functions, the Gabor function is proved to achieve the lower bound and performs the best analytical resolution in the joint domain [4]. This function is a Gaussian modulated by a sinusoidal signal and shown below:

$$\varphi(t) = \exp(-\alpha^2 t^2)\exp(j2\pi f0t) \qquad (3)$$

$$\Phi(f) = \sqrt{\frac{\pi}{\alpha}}\exp\left(-\frac{\pi^2}{\alpha^2(f-fo)^2}\right) \qquad (4)$$

Where α determines the sharpness and f_0 the is modulated centre frequency of (t), and Φ(f)is its Fourier transform. Fig.2shows the example of (t) with three different f_0 but the same α and their time-frequency analysis by Gabor transform. These three distributions have the same area but don't meet thematic-resolution requirement: the window size should depend on the centre frequency. To achieve this requirement, we substitute α with f_0/γ, where γ is a self-defined constant, and make the time duration of (t)dependent on the central frequency f_0.The generalized (t) with normalization of the maximum response in frequency domain is now defined as:

$$\varphi(t) = \frac{|f_0|}{\gamma\sqrt{\pi}}\exp\left(\frac{fo^2}{\gamma^2}t^2\right)\exp(j2\pi f_0 t) \qquad (5)$$

Fig.3. shows the example of this new-defined (t) with three different f_0 but the same α and their time-frequency analysis by Gabor transform. This 1-D Gabor function could be extended into 2-D form and also achieve the lower bound of uncertainty principle [5]. This 2-D Gabor function is defined as :

$$\varphi(x,y) = \frac{f^2}{\pi_\gamma \eta}\exp\left(-\left(\frac{f^2}{\gamma^2}X_r^2 + \frac{f^2}{\eta^2}Y_r^2\right)\right)\exp(j2\pi f x_r) \qquad (6)$$

$$xr = x\cos\theta + y\sin\theta, yr = -x\sin\theta + y\cos\theta$$

Where f is the frequency of the modulating sinusoidal plane wave and θ is the orientation of the major axis of the elliptical Gaussian. The 2-D Fourier transform ofφ(x), is shown below:

From the course [3], we know that a set of 1-D wavelets is defined as:

$$\psi(t,a,b) = \psi((t-a)/b) \qquad (7)$$

where $\psi(t)$ is the mother wavelet and a and b determines the temporal shifting and scaling of this function. This definition could be further extended into 2-D wavelet transform as:

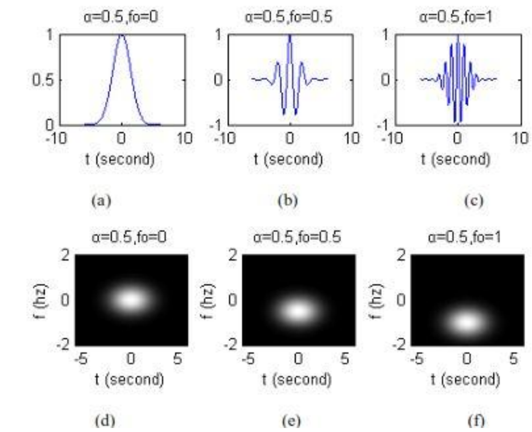

Figure.2. Example of (t) with three different f_0 = 0, 0.5, and 1 but the same α = 0.5 and their time-frequency analysis by Gabor transform, where (a)-(c) show the real part of (t) and (d)-(f) show the magnitude of the Gabor transform of $\varphi(\mathrm{t})$

$$\psi\theta\,(\mathrm{bx}, \mathrm{by}, \mathrm{x}, \mathrm{y}, \mathrm{x0}, \mathrm{y0}) = \frac{1}{\sqrt{\mathrm{bxby}}}\psi\theta\left(\frac{(x-x_0)}{b_x} + \frac{(y-y_0)}{b_y}\right) \quad (8)$$

where $\psi\theta$ (x, y) is the 2-D mother wavelet, with bx and by the scaling parameters,x0 and y0 the spatial shifting, and θ the orientation parameter. The 2-D Gabor function defined in Eq.6 meets this form and could be seen as a set of self-similar Gabor wavelets. The spatial shifting terms are missing in Eq.6 while these could be compensated by the convolution operation between this equation and the input image. To make φx, as a set of continuous wavelets, we should make sure that φx, y obeys the five constraints [3]: compact support, real, even symmetric or odd symmetric, vanishing moments, and admissibility criterion. The former three constraints are achieved by setting a magnitude threshold to φx, y and separate it into real and imaginary part, while the latter two need the DC-free modification to make this wavelet transform reversible and with at least one vanishing moment.

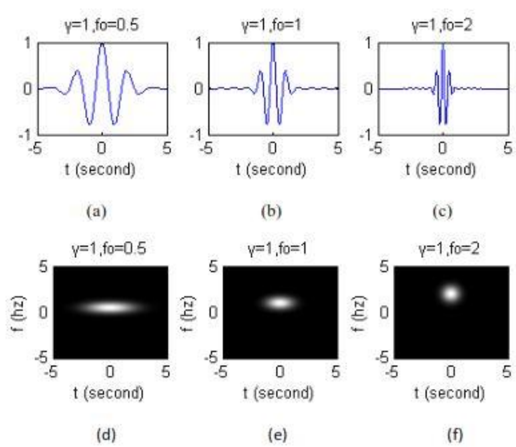

Figure.3. Example of (t) with three different f_0 = 0, 0.5, and 1 but the same α = 0.5 and their time-frequency analysis by Gabor transform, where (a)-(c) show the real part of (t)and (d)-(f) show the magnitude of the Gabor transform of φ(t) In practical cases, the Gabor wavelet is used as the discrete wavelet transform with either continuous or discrete input signal, while there is an intrinsic disadvantage of the Gabor wavelets which makes this discrete case beyond the discrete wavelet constraints: the 1-D and 2-D Gabor wavelets do not have orthonormal bases. If a set of wavelets has orthonormal bases, the inverse transform could be easily reconstructed by a linear superposition, and we say this wavelet transform provides a complete representation. The no orthonormal wavelets could provide a complete representation only when they form a frame [1]. The concepts of the frame is beyond the scope of this report because it's too theoretical, while in most of the applications, we don't really care about these

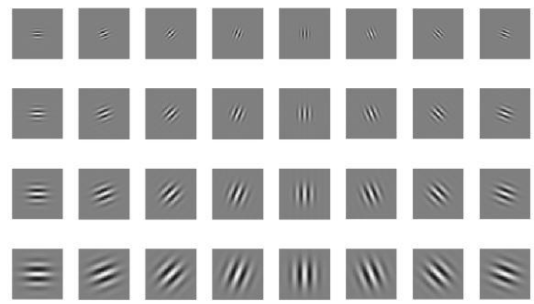

Figure.4. An example of the real part of Gabor wavelets with 4 scales and 8 orientations. The $fmax$ is set as 0.35 with γ = η = 1.2.

Orthonormal properties if the Gabor wavelets are used for ***"feature extractions"***. When extracting features for pattern recognition, retrieval, or computer vision purpose, the transformed coefficients are used for distance measure or compressed representation but not for reconstruction, so the Orthogonal constraint could be omitted [7]

3. PRINCIPAL COMPONENT ANALYSIS "PCA"

One of the simplest and most effective PCA approaches used in face recognition systems is the so-called Eigen face approach. This approach transforms faces into a small set of essential characteristics, Eigen faces, which are the main components of the initial set of learning images (training set). Recognition is done by projecting a new image in the Eigen face subspace, after which the person is classified by comparing its position in Eigen face space with the position of known individuals In general, we apply many transformations before loading. Indeed, the signal contains information useful to the recognition and only the relevant parameters are extracts. The model is compact representations of the signal which make ease the phase of recognition, but also reduce the quantity of data to be stored

$$\begin{pmatrix} a_{1,1} & \cdots & a_{1,m} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,m} \end{pmatrix} \longrightarrow \begin{pmatrix} a_{1,1} \\ \vdots \\ a_{n,1} \\ \vdots \\ a_{1,m} \\ \vdots \\ a_{n,m} \end{pmatrix}$$

Then, let the training set of face images be Γ1, Γ2, Γ3…,ΓM. The average face of the set is defined by Eq. (12)[5]:

$$\Psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i \quad (12)$$

Each face differs from the average by the vector Eq. (13):

$$\Phi\mathrm{i} = \Gamma\mathrm{i} - \Psi, \mathrm{i} = 1 \dots \mathrm{M} \quad (13)$$

In the next step the covariance matrix C is calculated according to Eq. (14):

$$C = \sum_{i=1}^{N} \phi_i \phi_t^2 = AA^T \qquad (14)$$

The matrix C is N2 by N2, and determining the N2 eigenvectors and Eigen values is an intractable task foe typical image sizes. We need a computationally feasible method to find these eigenvectors Eq. (15):

$$e_i = Av_i \qquad (15)$$
$$\lambda_i = \mu_i$$

From M eigenvectors (Eigen faces) ei, only M1 should be chosen, which have the highest Eigen values. The higher the Eigen value, the more characteristic features of a face does the particular eigenvector describe. Eigen faces with low Eigen values can be omitted, as they explain only a small part of characteristic features of the faces. After M1 Eigen faces ei are determined, the 'training' phase of the algorithm is finished. The process of classification of a new (unknown) face Γ new to one of the classes (known faces) proceeds in two steps. First, the new image is transformed into its Eigen face components. The resulting weights form the weight vector T
Equation [3]:

$$Wk = e_k^t(\Gamma_{new} - \Psi), k = 1 \ldots \ldots . M', \Omega T = [w1, w2, \ldots, wM']$$

The weights form a vector T = [w1, w2... wM'] that describes the contribution of each Eigen face in representing the input face image, treating the Eigen faces as a basis set for face images. The vector may then be used in a standard pattern recognition algorithm to find which of a number of predefined face classes, if any, best describes the face. The used method for determining which face class provides the best description of an input face image is the support vector machines: SVM.

4. SUPPORT VECTOR MACHINES

Support vector machines are learning machines that classify Data by shaping a set of support vectors [10]. SVMs provide a Generic mechanism to robust the surface of the hyper plane to The data through. Another benefit of SVMs is the low expected Probability of generalization errors Moreover, once the data is classified into two classes, an appropriate optimizing algorithm can be used if needed for feature identification, depending on the application [8]. SVM creates a hyper-plane between two sets of data for classification face belongs to the train database and face doesn't belong to the train database. Input data X that fall one region of the hyper-plane, (XT•W– b) > 0, are labelled as +1 and those that fall on the other area, (XT•W–b) < 0, are labelled as -1.Intuitively, this classifier is a hyper plane that maximizes the margin error, which is the sum of the distances between the hyper plane and positive and negative examples closest to this hyper plane. We consider the example in (a) where there are many possible linear classifiers that can separate the data, but there is only one that maximizes the margin shown in (b). This Classifier is termed the optimal separating hyper-plane (OSH).[5]

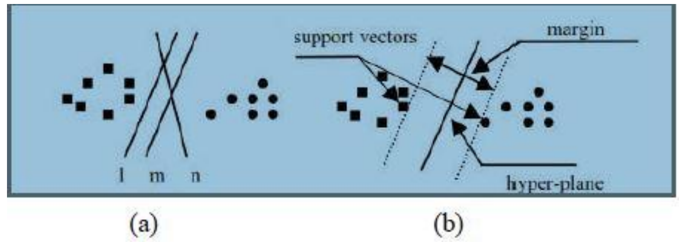

Figure.5. SVM Vectors

5. EXPERIMENT AND RESULTS

Our system is a system of identification, so the system must Guess the identity of the person. The system compares the vector characteristic of the test image with the different models Contained in the database (type of problem 1: n) using the Euclidean distance or the SVM classifier In identification mode, we talk about open problem since its assumed that an individual has no model in the database (Impostor) may seek to be recognized. So, we're doing a study on the database of learning for the appropriate threshold θwhich allows us to identify whether that person is in our database or not he is an imposter. The execution of the biometric system is estimated by measuring the rate of false acceptance (FAR) Eq. (16), the rate of false rejection (FRR) Eq. (17) and the equal error rate (ERR)

$$FAR = \frac{false\ acceptance\ numbers}{number\ of\ impostors} \qquad (16)$$

Figure.5. FRGC Face

Figure.6. ORL Face

$$FRR = \frac{false\ rejection\ numbers}{number\ of\ customers} \qquad (17)$$

$$EER = \frac{false\ acceptance\ number + false\ rejection\ number}{total\ number} \quad (18)$$

The FRGC consisted of progressively difficult challenge problems. Each challenge problem consisted of a data set of facial images and a defined set of experiments. One of the impediments to developing improved face recognition is the lack of data. The FRGC challenge problems include sufficient data to overcome this impediment. The set of defined experiments assists researchers and developers in making progress on meeting the new performance goals [6]. The ORL have ten different images of each of 40 distinct subjects. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses) [6].The design of a system of pattern recognition requires abas is of learning and a validation to assess the performance of the method. The FRGC distribution consists of six experiments. In our work, we use two experiments 1 and 4. In experiment 1, the gallery consists of a single controlled still image of a person and each probe consists of a single controlled still image. Experiment 1 is the control experiment [5]. In experiment 4, the gallery consists of a single controlled still image, and the probe set consists of a single uncontrolled still image [6].ROC graphs are two-dimensional graphs in which FRR and FAR rate is plotted on the Y axis and Threshold is plotted on the X axis. The figure 7 below shows the ROC curve applied in the FRGC database:

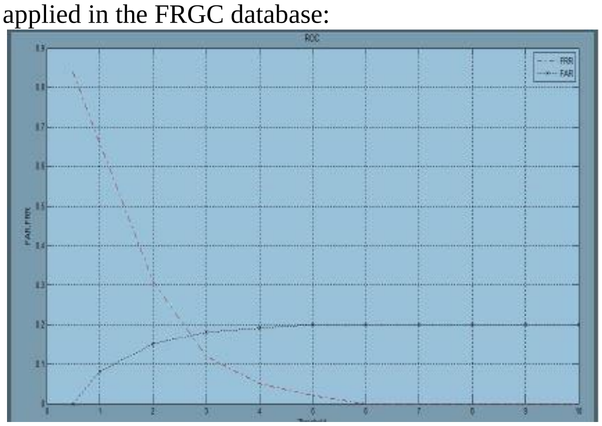

Figure.7. curve ROC of the ORL database

We note that both error rate FRR and FAR are inversely proportional increases if FRR increases FAR decreases, therefore we must choose a compromise between FAR and FRR. We can conclude from this figure that the threshold is 2.7*1013

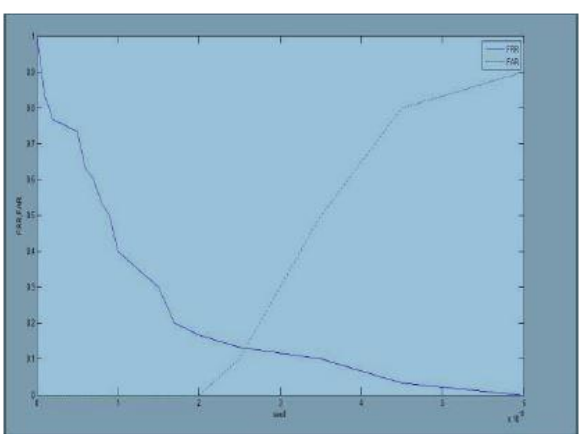

Figure. 8. Curve ROC of the ORL database

In the first part of experiment we have use only the algorithm PCA. The input image is a face image detected with MATLAB Simulink and normalized geometrically so the size of the face is 64*64 pixels. Table 1 gives the equal error rate after using PCA with the experience 1 and the experience 4 of the FRGC database. The first protocol P1 evaluates performance comparison of images (reference and tests) belonging to sessions to acquire the same semester. The second protocol P2 evaluates performance testing sessions belonging to image acquisition two consecutive semesters and one last test P3 performance of image reference and test, separated by a year. Tables I and II list the equal error rates for the FRGC and ORL databases, respectively.

Table .1. Err of PCA for the FRGC database

		EER
Exp 1	P1	0.26
Exp 1	P2	0.53
Exp 1	P3	0.41
Exp 2	P1	0.81
Exp 2	P2	0.8
Exp 2	P3	0.9

Table.2. Err of PCA for the ORL database

	EER
30 features	0.2

According to tables I and II, we have EER very high which makes the application less reliable. This is due to the influence of the change of light and change poses to our database on Eigen face, which leads us to try to reduce its error rate with using Gabor features. For the second table, the error rate has clearly decreased. It notes that use of the magnitude and the phase to represent face has an important influence on the performance of the application and the improvement of error rates. Tables III and IV give the equal error rate after using the magnitude and phase of Gabor to extract the characteristic vector, the algorithm of recognition PCA and for classification we use Euclidian distance.

Table.3. Error rate for fusing magnitude et phase of GABOR, PCA and Euclidien distance for the FRGC database

		EER
Exp 1	P1	0.17
Exp 1	P2	0.33
Exp 1	P3	0.20
Exp 2	P1	0.26
Exp 2	P2	0.3
Exp 2	P3	0.4

Table.4. Err for fusing magnitude ET phase of GABOR, PCA and Euclidien distance for the ORL database

	EER
30 features	0.005

Tables V and VI give the equal error rate after using the magnitude and phase of Gabor to extract the characteristic vector, the algorithm of recognition PCA and for classification we use SVM.

Table.5. Error rate for fusing magnitude et phase of GABOR, PCA and SVM for the FRGC database

		EER
Exp 1	*P1*	0.09
Exp 1	*P2*	0.18
Exp 1	*P3*	0.11
Exp 2	*P1*	0.13
Exp 2	*P2*	0.15
Exp 2	*P3*	0.20

7. CONCLUSION

The algorithm PCA is a global method using primarily the grayscale pixels of an image. The simplicity to implement this algorithm contrasts with a strong sensitivity to changes in lighting, poses and facial expression. That is why we increase the number of poses for each person. Nevertheless, the PCA requires no a prior knowledge on the image. Our approach consists on combining the magnitude and the phase of Gabor to extract the characteristic vector, the algorithm PCA for recognition. The principle that you can construct a sub-vector space retaining only the best eigenvectors, while retaining a lot of useful information, makes the PCA an algorithm effective and commonly used in reducing dimensionality where it can then be used to upstream other algorithms to improve the results of our application. To conclude, we can say that the recognition of individuals remain a complex problem, in spite of current active research. There are many conditions real, difficult to model and envisage, which limit the performances of the current systems in terms of reliability and real time. As future work, we propose the implementation of such an algorithm on a target technology in order to benefit from the performances provided by this technology.

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