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A PROPOSED GENERALIZED EIGENFACES SYSTEM FOR FACE RECOGNITION BASED ON ONE TRAINING IMAGE

一种基于一次训练图像的广义特征识别系统

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Abstract

This paper discusses the results of a study that aimed to develop an eigenface technique known as (PC) 2A that collect the image of the original face with its vertical and horizontal projections. The basic components of the image were analyzed in the image enrichment section. An evaluation of the proposed method demonstrates that it costs less than the standard eigenface technique. Moreover, the experimental results show that a front-end database that has a gray level for each person has one training image; thus, in terms of accuracy, it was possible to get a 3-5% result for the proposed (PC)2A, which is higher than the precision of the standard eigenface technique. The main objective of this paper is to demonstrate the weaknesses and strengths of the facial recognition approach as an identifier known as eigenfaces. This aim was achieved by using the principal components analysis algorithm based on the images of previously stored training data. The outcomes show the strength of the proposed technique, in which it was possible to obtain accuracy results of up to 96%, which in turn provides support for developing the technique proposed in this paper in the future because this work is of great importance in the field of biological treatments, the need for which has significantly increased over the last 5 years.

Keywords: Eigenface, Principal Components Analysis, Image Configure, Projection Map

摘要 本文讨论了一项研究的结果，该研究旨在开发一种称为（个人电脑）2 一个的特征脸技术，该技术可收集具有垂直和水平投影的原始面孔的图像。在图像丰富部分中分析了图像的基本成分。对所提出方法的评估表明，它的成本低于标准特征脸技术。实验结果表明，每个人都具有灰度的前端数据库具有一个训练图像。因此，就准确性而言，所提出的（个人电脑）2 一个可能会获

得 3-5%的结果，该结果要比标准本征面技术的精度更高。本文的主要目的是证明面部识别方法作为识别为特征脸的标识符的弱点和增强之处。通过使用基于先前存储的训练数据的图像的主成分分析算法来实现此目标。结果表明了所提出技术的实力，其中可以获得高达 96%的准确度结果，这反过来为将来开发本文提出的技术提供了支持，因为这项工作在当今的研究中非常重要。在过去的 5 年中，对生物治疗领域的需求已大大增加。

关键词: 特征脸，主成分分析，图像配置，投影图

I. INTRODUCTION

Over the past 20 years, facial recognition has been an ongoing research topic in the field of pattern recognition and computer vision. Face recognition techniques are classified as technology based on engineering features and as technology based on a template, as suggested by Brunelli and Poggio [1]. These techniques have led to the development of many new methods, which can be further categorized as the procedures that are widely utilized for coordinating a versatile pack chart [2] and the dynamic appearance model [3]. The subset classification incorporates the most well-known procedure, which is an eigenface [4]. It is important to note that neural networks are widely used in the bodily region of the face [5]. Eigenface technology emerged in the 20th century. It was used commercially in the 1990s, and it combines the science of analysis and the measurement of biological data, which has a dynamic character in the mechanisms of computer vision; this is useful in the biometric field [6]. The main objective of facial recognition is to verify or identify a person's identity through photographs or by using video stored on a database of faces. It should be noted that many research efforts have focused on how to improve the efficiency of facial recognition systems [7]. Although most techniques ignore a potential problem in the face database, which is that more than one image per person might be stored, due to the limitations of the storage capacity of the systems or the difficulty in collecting samples, all traditional methods, such as Fisherfaces [8], [9] and eigenfaces [4], [10] have low facial recognition performance.

Subspace technologies are characterized by their fast facial recognition ability and their good recognition performance. However, they suffer from some of the defects that are apparent in standard eigenface technology. The face image is represented as dots in a high-dimensional area. In the new method proposed in the present study, some of the bad things that result from dropping the Principal Components Analysis (PCA) are efficient by posting dots but not thinking about how to assign points to different categories. The role of technology in dealing with this problem is highlighted by considering the points that are needed to obtain the results. However, this requires two images of each person in the training database, which is not the case in the real world where this condition cannot be met in law enforcement scenarios, which requires only one image of the person for training database [33].

In this paper, we introduce an idea to improve standard eigenface technology, called (PC)2A, which is a major component analysis of the projected image. This technology, in turn, costs less than the standard eigenface innovation. Moreover, the study's results show that, in the event that one picture is rigidly trained for each face, (PC)2A is clearly superior to standard eigenface technology.

II. LITERATURE REVIEW

Recently, face recognition techniques have developed significantly, with several techniques emerging, for example:

Thorat [11] has identified a major weakness that is that many systems are less effective if facial expressions contain significant differences, while other cases such as sunglasses, poor lighting, partially covered face, and long, thick, long hair, the FR does not work well and the result is a poor picture.

This opinion was supported by Avexander and Richert-Boe [12] as these researchers emphasized that the limitation in image quality, such as low-quality images and old images that are used in comparison, and this affects the effectiveness of the FR, and this generates a high difficulty on the system, as well as speaking about "images that are clear on both sides of the equation." Required in order to produce an exact match "

Pantic and Rothkrantz [13] adopted the technique of analyzing facial expression so that we were able to design and implement a system capable of performing an automatic analysis that can recognize the face, through facial detection and then conduct facial expression analysis and then finally develop a mechanism to extract information facial expressions.

Daugman [14] has many important and critical insights involved in the facial recognition system effectively, While the comprehensive survey was carried out by Zhao et al. through all modern techniques

Zhao et al. [15], Fromherz [16] and Chellappa et al. [17] have done a great job of researching new and good surveys about human and machine-recognition in faces.

Often template-based techniques follow the eigenface method of any micro-space, and the technique relies on PCA conversion (Loève-Karhunen) [4]. Any major component analysis is then inserted into the facial processing by Sirovich and Kirby [18], where we were able to prove that the best coordinate system called eigenfaces, which enabled them to represent any particular aspect, and from here emerges the importance of eigenfaces to the average contrast between a group of faces here we were able to prove that the best coordinate system called eigenfaces, which enabled them to represent any particular aspect, and from here emerges the importance of eigenfaces to the average contrast between a group of faces.

III. Effect of Factors in Face-Recognition

The mechanism of recognizing the human face in both video clips and pictures is a difficult effort, in reality, there are many techniques to implement this requirement, but there is no technology to implement this work by 100% and this is due to the challenges facing this system, these factors are divided into two internal (Facial expressions and aging) and external (Pose-variation, lightening-condition) categories [19], [34].

A. Aging

It is one of the main factors that have a clear effect on facial recognition techniques because they cause chaos of algorithms. Permanence is a state of basic quality for any measurement of the Biologi being treated as a biometric, While the face is a mixture between the tissues of the body and bones and facial muscles, when these muscles contract, they work to distort the face (features), which leads to aging to large changes such as wrinkles and face shape over time [20], so it is very important that the identification systems of this obstacle (aging) and the research that dealt with this factor gained a lot of popularity [3].

B. Facial Expression

Facial expressions are a means of non-verbal communication because it is expressions as a way of conveying messages, in spite of these expressions, there is ambiguity in facial recognition systems when they differ, Facial expressions reflect people's attitudes and different moods, as well as changing face geometry. this makes the system not recognize the face, so the researchers focused their work on crossing this problem by taking facial adjustments into account [21], [22], tough techniques to deal with this issue are muscle-base techniques, a basic approach model, and a motion-based-approach [23].

C. Pose-Variation

One of the main obstacles we face in the face recognition system is the Pose-variance, there is no similar situation in each image capture process, which creates a problem in recognizing faces and distinguishing them, in image that take in different situations, in this way, techniques that deal with Pose-variance can be divided into two types, recognize faces by positioning and multi-view recognizing faces, we can consider this feature (multi-face recognition), as a front face recognition facility, this takes the image of the exhibition of each image, in this area the field is still open to researcher [24], [25].

D. Partial-Occlusion

There are artificial and natural obstructions in some images caused by Partial-Occlusion, which lead to the classification of methods of facial recognition into different categories including existing roads on a partial basis, existing methods, and feature-based on geometric pattern [25].

E. Illumination Effect

The face recognition system is highly sensitive to Illumination Effect, which has taken an increasing interest in researchers' work, this makes it difficult to identify the person or more of the video or still images, images that have a unified background environment are easy to extract, while images with an unregulated environment need techniques that deal with variation due to shadows, researchers have worked hard to overcome this obstacle, three techniques have been proposed to deal with this problem, Gray-level, gradient and face-reflection-field [26], [27].

III. BASIC THEORY

In our proposal, some basic principles have been adopted to improve face recognition through one-image training.

A. Eigenface

Eigenface is based on the principle of viewing each image as a vector of features in a high-dimensional space by using the density of each pixel as a single-feature in addition to connecting image rows. It must be noted that these dimensions are n which are very large, based on several-thousand, here is the basic function of PCA, which is to reduce the dimensions-n by mapping the vector-x into a dimensions-m space (m < n).

The x vector can be rounded as a linear combination of a vector, (I = 1, 2, ...m) as in equation 1.

$$\bar{X}. = \sum_{i-1}^{\bar{M}} Z_i u_i \qquad (1)$$

Here through this equation are obtained the best approximation such as those that reduce the difference between X^ and X this is measured by the square error mean, the matrix covariance of (x) represents by ∑_X.

$$\sum\nolimits_X = E[(X - \hat{X})(X - \hat{X})^T \qquad (2)$$

where X¯ represents an average vector X. It has been proven bishop [31], the best user interface u_i (i = 1, 2, 3……., m) It is an eigenvector unit that is associated with values greater than eigenvalues ∑_X. These units eigenvectors refers to eigenfaces [4]. Which are used to recognition the face, here corresponding dimensional-m vector v = [v1, v2….vm] As advantages extracted by PCA, which are later used to recognition-process of the face, it should be noted that (m < n) this includes that the dimensionality will decrease dramatically and which leads to a lower problem ratio, This is what happens in real-world applications where ∑_X. is replaced by the sample matrix scatter. for determining the appropriate value-form, the eigenvalues values are compiled to ∑_X. in descending order. It is assumed that there are eigenvalues values (λ1, λ2, ….λn) where: λ1 the biggest eigenvalues as for ゝn is the youngest. M is then identified as an initial integer and θ which is a predetermined threshold, according to Bishop [28], this is in Equation 3.

$$i = \frac{\sum_{i=1}^{m} \lambda_i}{\sum_{i=1}^{n} \lambda_i} \geq \theta \qquad (3)$$

This is what Bishop [28] said to follow the standard test corresponding in equation 3, m is the largest eigenvectors can be captured (θ X100%) this means that variation in X.

θ should be set to a value greater than 0.9 and this will easily capture the variance in input data, and on this basis, the features obtained from the PCA (expressive features), then drop down PCA spreads points efficiently, but it does not take into account how to assign points to different categories, to resolve this issue, information is used in class labels. However, suffering persists because the learning technique under supervision may not be effective when there is one training image for each person.

B. Generalizing Eigenface

According to the point of view Jain et al. [29] the model statistical system is divided into three consecutive stages (preprocess, extraction, selection or learning). Most of the research currently focuses on the last two phases of eigenface while a few works focus on the first phase pre-process phase. In this paper, we suggest (PC)2A to recognition the face with one image per person. The aim of this technique is to design the pre-processing technology for use with eigenface technology. Here comes the advantage of the proposed technology, where (PC)2A combines the original face image with its first-class display. After this, PCA performs the custom version [30]. Here we follow the style of (PC)2A in an innovative and unique way to get facial recognition. Sequence The following equations describe the process of Generalizing eigenface, depending on these vectors

P(x, y) represents the intensity of image size $(N_1 X N_2)$. When X ∈ $(1, N_1)$ and Y ∈ $(1, N_2)$ also P(x, y) ∈ (0, 1). Horizontal and vertical projections can be represented as follows:

$$H_p(y) = \sum_{X=1}^{N_1} P(x, y) \qquad (4)$$

$$V_p(x) = \sum\nolimits_{y=1}^{N_2} P(x, y) \qquad (5)$$

Now we can select the projected map Mp(x, y) for P(x, y) as

$$M_p(x, y) = \frac{V_p(x) H_p}{N_1 N_2 \bar{P}} \qquad (6)$$

where $\bar{P}$ represents the density of the image as

$$P = \frac{\sum_{x=1}^{N_1} \sum_{y=1}^{N_2} P(x, y)}{N_1 N_2} \qquad (7)$$

In order to determine the combined version of the projection, we must work on P(x,y) as refer to equation (8).

$$P_a(x, y) = \frac{P(x, y) + aM_p(x, y)}{1 + a} \quad (8)$$

To understand the projection-map and the version combine of the image, look at the suggested example in Figure 1 and through which it is set α to 0.25. Where Pα (x, y) maybe you fall off [0, 1], the image display may be distorted and the result of recognition will not be affected by image distortion.

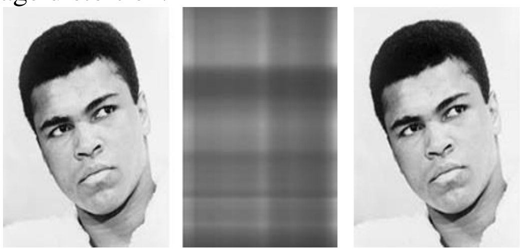

Figure 1. An example of a projection-map and a combined projection image

In order to get a better view, the exact image is selected and then modified in Figure 1 according to the following:

1) Basic Components and Basic Analysis

Easy to prove that $(P_a(x, y), M_p(x, y)$ and P(x, y)) owning properties below:

1) Mean intensity equals average intensity $P(x, y) = M_p$(x, y).

2) When α ≠ -1, The Mean intensity equals average intensity $P(x, y) = M_p$(x, y).

3) If α approaching 0, It is $(P_a(x, y)$ exactly equal P(x, y).

4) If α approaching infinity, It is $P_a(x, y)$ approaching P(x, y).

5) The internal dimension for $M_p(x, y)$ Be as little as possible when $(N_1 + N_2 - 1)$.

6) The internal dimension for $M_p(x, y)$ Be smaller than we expect P(x, y).

It should be noted here that the average-intensity determines the value $M_p(x, y)$, so whenever α is a reasonable proportion is not large, Merge $M_p(x, y)$ to P(x, y), this will blur the original image while retaining the key information for image. This version $P_a(x, y)$ is expected to work more efficiently than standard-eigenface-technology, against changes illumination, occlusion, expression.

2) Image Configure

In this paper, we compare ((PC) 2A) with standard-eigenface-technology using a front-end (gray) database of 600 images of 300 people. There are 91 women and 509 males. Each has two images (fa – fb). This includes all different facial expressions, in the case of training, fa images are used as test probes (training gallery), the test is random for all images depending on the FERET face-database [31]. It should be noted here that there are no special criteria for the test, that is why in our experience these facial images are often varied. For example (faces with different races, different ages, different sex, different occlusion, different lighting, different expression, different scale). This in itself generates a big problem because it makes it harder to recognize the face. Figure 2 contains some initial images from the database.

Figure 2. Raw-images in the FERET database

Refer (PC) 2A and standard-eigenface-technology indicate that they represent an (m dimensional) vector. Where m is calculated from Equation 3. In our proposed technique is proposed 0.9 if not mentioned. It should be noted here that our PC (PC) 2A has another parameter, the blend α parameter, which will be assigned a value of 0.25. The process of normalization of facial images takes place before exposure to micro-space techniques. Normalization of facial images meets certain restrictions so that the face can be trimmed appropriately. These limitations are the separation between the eyes is a fixed-esteem, while the line between the eyes is constantly parallel to the even pivot as well as the image size is fixed, it should be noted here that the identification of eyes with high efficiency is very important. The dimensions of the raw-images are initially 256 x 382 pixels, the distance between the eyes (40-60) pixels, and these sizes change through the bilinear-method.

The images at the moment of capture are of a size (60 x 60) while the eyes have a distance of (28) pixels. After you select the spaces and draw the frame of the captured images, when viewing the probe, corresponded-Vector is created by eigenfaces. Thus, we can calculate all the angles of each image in the gallery and the characteristic vector of the object, after this procedure the images will be arranged based on the ascending order in which you have the angles. This is the recognition at the top which expresses the identity of the image. When testing our technology and comparing it with many techniques that give the same pattern based on the FERET test [31], [32], it is considered the best in the right match and correct answer.

C. Projection Map

Horizontal and vertical projections are used very extensively for face recognition tasks, In the case of combining these projections the interest appears in the formation of the projection map. this point is characterized by its exhibit for this is used MP (x, y), as an input to various databases, thus we get the highest match as in Figure 3. While the number of users from eigenfaces is displayed in Figure 4. Here θ should be set to 0.9. When we draw attention to Figure 3 we notice that when rendering a projection-map a place a face image itself to the standard- eigenface-technology. Best match ratio in matching is always better than 70%. However, our experience in Figure 4 shows that to reach 90% of the total variance we need a few eigenfaces, even if the number is 300 (database), we need 14 eigenfaces, this is evidence of the strength of the projection scheme used in facial recognition, an important feature that supports Eigenfaces' efficiency is that the projection map focuses on the features of the motherboard and this, in turn, contributes greatly to the success of the PC (2A).

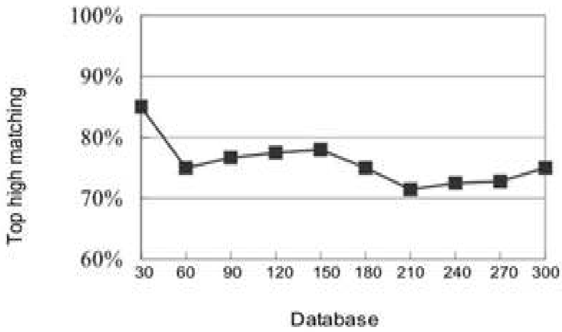

Figure 3. Top high matching rate from standard-eigenface-technology on projection-map

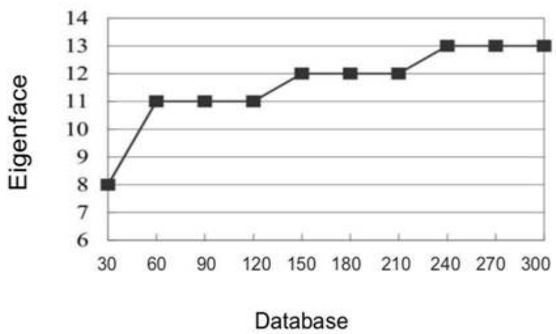

Figure 4. Number of users from standard-eigenface-technology on projection-map

Note the effect of α on the efficiency of PC (2A) (offer the combination-parameter), to illustrate this effect, we conduct some experiments for PC(2A) with values α which are different. Figure 5 shows PC(2A) technology and its use for a number of forms eigenfaces. Figure 6 shows the highest match rate. The database used in this procedure contains 98 images, which in turn are a suitable subset.

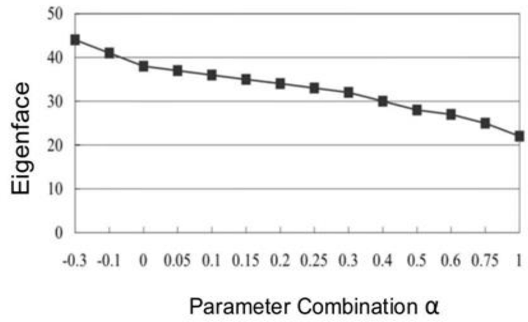

Figure 5. PC(2A) technology and its use for a number of forms eigenfaces with a parameter combination different values (i.e α)

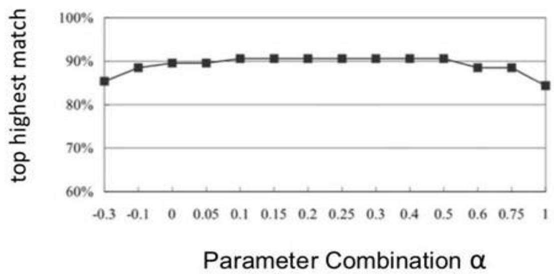

Figure 6. The top highest match rate of PC(2A) technology and its use for a number of forms eigenfaces with a parameter different values (i.e α)

To minimize dimensions (PC) 2A we increase the α because they greatly affect the reduction of dimensions, thus the number of eigenfaces used is clearly decreasing. These are additional features added to the balance of our experience, because the lower the eigenfaces, the lower the cost of computation, the lower the cost of storage, the lower processing. This is shown in Figure 5. A value should be chosen for α because the greater the value of α, the higher the recognition efficiency and then the lower the end. This indicates that there must be a suitable value for α to be selected for the performance of PC 2A. This is illustrated in Figure 6.

IV. Result

First, we have to compare the efficiency of the recognition between our technique (PC) 2A and eigenface standard through the results given as the database starts to gradually increase from 30 to 300 with 30 (interval). Figure 7 shows the nature of the results, where the developed technology (PC) 2A and standard eigenface technology are described as standard and expansion individually, The quantity of eigenfaces utilized has been resolved by Equation 3. It is wonderful to note that Figure 7 shows the top three match rates and does not match only the top.

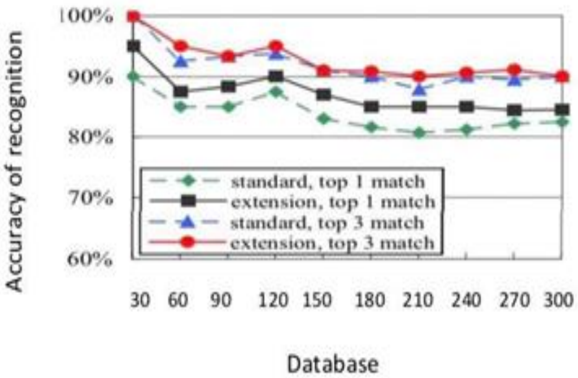

Figure 7. Efficient performance recognition

We conclude from Figure 7 that PC 2A is superior to eigenface when it comes to the top highest match. Recognition accuracy is approximately 3% - 5% superior to eigenface technology, we can also see the superiority of PC (2A) technology on eigenface when it comes to the top three matching rates in Figure 7. When performing the k-match rates (for comparison), the best performance is for PC (2A) for all k values. At worst, the tests are equally efficient.

Here we note that the difference in performance between the two experiments is quite obvious at k > 10. The analysis of the results as shown in Figure 8 is done by comparing the number of eigenfaces used by PC 2A and eigenfaces that appear when you start increasing the size of the face database from 30 to 300 with 30 (interval).

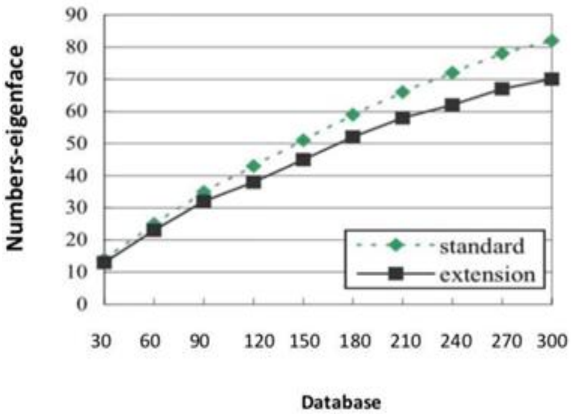

Figure 8. Eigenfaces used and number

V. CONCLUSION

Today, facial recognition techniques have evolved and they work efficiently to recognize the front part of a person's face (grey-level). To achieve facial recognition, these techniques require two images per person for the training data. That is the least amount required by this type of technology. In this paper, we focused on the idea of eigenface standard technology and we proposed a new version of this idea and applied it to (PC)2A technology. In the proposed method, emphasis is placed on the choice of the advantage or the learning phase in the patterns of pattern recognition rather than on the extraction of facial attributes. Thus, what is new is the focus on the issue of pre-treatment by smoothing the image of the original face. This is done through the process of tears with horizontal and vertical projections. Furthermore, in the proposed method the cost of computation is less than the cost needed for standard eigenface technology.

Finally, In terms of the efficiency of our proposed method, very high precision has been achieved, which is higher than that of the standard self-interface technology.

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REFERENCES

[1] BRUNELLI, R. and POGGIO, T. (1993) Face recognition: Features versus templates. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 15 (10), pp. 1042-1052.

[2] WISKOTT, L., FELLOUS, J.-M., KRUGER, N., and VON DER MALSBURG, C. (1997) Face recognition by elastic bunch graph matching. In: *Proceedings of the International Conference on Image Processing, Santa Barbara, California, October 1997.* Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.

[3] LANITIS, A., TAYLOR, C.J., and COOTES, T.F. (2002) Toward automatic simulation of aging effects on face images. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 24 (4), pp. 442-455.

[4] TURK, M. and PENTLAND, A. (1991) Eigenfaces for recognition. *Journal of Cognitive Neuroscience,* 3 (1), pp. 71-86.

[5] VALENTIN, D., ABDI, H., O'TOOLE, A.J., and COTTRELL, G.W. (1994) Connectionist models of face processing: A survey. *Pattern Recognition,* 27 (9), pp. 1209-1230.

[6] *Definition "Biometrics"*. [Online] Search Security. Available from: https://searchsecurity.techtarget.com/definition/biometrics [Accessed 10/01/20].
[7] MOSSLAH, A.A. and REYADH, H. (2018) 3DMM Fitting for 3D Face Reconstruction. *Journal of Engineering and Applied Sciences,* 13 (24), pp. 10482-10489.
[8] BELHUMEUR, P.N., HESPANHA, J.P., and KRIEGMAN, D.J. (1997) Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection. *IEEE Transactions on Pattern Analysis & Machine Intelligence,* 19 (7), pp. 711-720.
[9] ZHAO, W., CHELLAPPA, R., and PHILLIPS, P.J. (1999) *Subspace Linear Discriminant Analysis for Face Recognition.* College Park, Maryland: University of Maryland.
[10] SIROVICH, L. and KIRBY, M. (1987) Low-dimensional procedure for the characterization of human faces. *Journal of the Optical Society of America A,* 4 (3), pp. 519-524.
[11] THORAT, S.B., NAYAK, S.K., and DANDALE, J.P. (2010) Facial recognition technology: An analysis with scope in India. *Journal of Computer Science and Information Security,* 8 (1). Available from https://arxiv.org/ftp/arxiv/papers/1005/1005.4263.pdf.
[12] AVEXANDER, D. and RICHERT-BOE, J. *Ethics of Facial Recognition Technology*. [Online] Available from: http://www.ethicapublishing.com/ethics/4CH11.pdf [Accessed 14/01/20].
[13] PANTIC, M. and ROTHKRANTZ, L.J. (2000) Automatic analysis of facial expressions: The state of the art. *IEEE Transactions on Pattern Analysis & Machine Intelligence,* 22, pp. 1424-1445.
[14] DAUGMAN, J. (1997) Face and gesture recognition: Overview. *IEEE Transactions on Pattern Analysis & Machine Intelligence,* 19 (7), pp. 675-676.
[15] ZHAO, W., CHELLAPPA, R., PHILLIPS, P.J., and ROSENFELD, A. (2003) Face recognition: A literature survey. *ACM Computing Surveys,* 35 (4), pp. 399-458.
[16] PUJOL, J.V., LUMBRERAS, F., and VILLANUEVA, J.J. (2001) Topological principal component analysis for face encoding and recognition. *Pattern Recognition Letters,* 22, pp. 769-776.
[17] CHELLAPPA, R., WILSON, C.L., and SIROHEY, S. (1995) Human and machine recognition of faces: A survey. *Proceedings of the IEEE,* 83 (5), pp. 705-740.
[18] KIRBY, M. and SIROVICH, L. (1990) Application of the Karhunen-Loeve procedure for the characterization of human faces. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 12 (1), pp. 103-108.
[19] GONG, S., MCKENNA, S.J., and PSARROU, A. (2000) *Dynamic Vision: From Images to Face Recognition*. London: Imperial College Press.
[20] PARK, U., TONG, Y., and JAIN, A.K. (2010) Age-invariant face recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 32 (5), pp. 947-954.
[21] LI, X., MORI, G., and ZHANG, H. (2006) Expression-invariant face recognition with expression classification. In: *Proceedings of the 3rd Canadian Conference on Computer and Robot Vision, Quebec, June 2006.* Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.
[22] RIAZ, Z., MAYER, C., WIMMER, M., BEETZ, M., and RADIG, B. (2009) A model-based approach for expressions invariant face recognition. In: TISTARELLI, M. and NIXON, M.S. (eds.) *Advances in Biometrics. ICB 2009. Lecture Notes in Computer Science,* Vol. 5558. Berlin, Heidelberg: Springer, pp. 289-298.
[23] MURTAZA, M., SHARIF, M., RAZA, M., and SHAH, J.H. (2013) Analysis of face recognition under varying facial expression: a survey. *International Arab Journal of Information Technology,* 10 (4), pp. 378-388.
[24] HUANG, F.J., ZHOU, Z., ZHANG, H.-J., and CHEN, T. (2000) Pose invariant face recognition. In: *Proceedings of the 4th IEEE International Conference on Automatic Face and Gesture Recognition, Grenoble, March 2000.* Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.

[25] SHAH, J.H., SHARIF, M., RAZA, M., and AZEEM, A. (2014) Face recognition across pose variation and the 3S problem. *Turkish Journal of Electrical Engineering & Computer Sciences,* 22 (6), pp. 1423-1436.
[26] WEI, X., LI, C.-T., and HU, Y. (2012) Robust face recognition under varying illumination and occlusion considering structured sparsity. In: *Proceedings of the 2012 International Conference on Digital Image Computing Techniques and Applications, Fremantle, December 2012.* Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.
[27] SHARIF, M., ANIS, S., RAZA, M., and MOHSIN, S. (2012) Enhanced SVD Based Face Recognition. *Journal of Applied Computer Science & Mathematics,* 12, pp. 49-53.
[28] BISHOP, C.M. (1995) *Neural Networks for Pattern Recognition*. New York: Oxford University Press.
[29] JAIN, A.K., DUIN, R.P.W., and MAO, J. (2000) Statistical pattern recognition: A review. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 22 (1), pp. 4-37.
[30] WU, J. and ZHOU, Z.-H. (2002) Face recognition with one training image per person. *Pattern Recognition Letters,* 23 (14), pp. 1711-1719.
[31] PHILLIPS, P.J., WECHSLER, H., HUANG, J., and RAUSS, P. (1998) The FERET database and evaluation procedure for face-recognition algorithms. *Image and Vision Computing,* 16 (5), pp. 295-306.
[32] MOSSLAH, A.A. (2018) Telemedicine Medical Image Compression Based on ROI (A Case Study of Spine Medical Images). *Journal of Global Pharma Technology.* Available from http://www.jgpt.co.in/index.php/jgpt/article/view/811.
[33] LUAIBI, M.K. and MOHAMMED, F.G. (2019) Facial Recognition Based on DWT – HOG – PCA Features with MLP Classifier. *Journal of Southwest Jiaotong University,* 54 (6). Available from http://jsju.org/index.php/journal/article/view/400.
[34] BODRYSHEV, V.V., ABASHEV, V.M., KORZHOV, N.P., and TARASENKO, O.S. (2018) Study of Interaction of a Jet with Supersonic Flow on the Parameter of the Intensity of the Video Frame Image. *Periódico Tchê Química,* Special Issue 1, pp. 348-358.

参考文:

[1] BRUNELLI， R. 和 POGGIO， T.（1993）人脸识别：特征与模板。电气工程师学会模式分析与机器智能交易，15（10），第 1042-1052 页。
[2] WISKOTT，L.，FELLOUS，J.-M.，KRUGER，N. 和 VON DER MALSBURG, C.（1997）通过弹性束图匹配进行人脸识别。于：1997 年 10 月在加利福尼亚州圣塔芭芭拉举行的图像处理国际会议论文集。新泽西州皮斯卡塔维：电气与电子工程师协会。
[3] A. LANITIS，C.J。TAYLOR，T.F。COOTES。（2002）对面部图像老化效果的自动模拟。电气工程师学会模式分析与机器智能交易，24（4），第 442-455 页。
[4] TURK， M. 和 PENTLAND， A.（1991）的特征脸。认知神经科学杂志，3（1），第 71-86 页。
[5] VALENTIN， D.， ABDI， H.， O'TOOLE， A.J. 和 COTTRELL， G.W.（1994）人脸处理的连接主义模型：一项调查。模式识别，27（9），第 1209-1230 页。
[6] 定义“生物识别”。[在线]搜索安全性。可从以下网站获得：https://searchsecurity.techtarget.com/definition/biometrics [访问时间 10/01/20]。
[7] MOSSLAH，A.A。和 REYADH，H.（2018）用于 3D 人脸重建的 3 数字万用表拟合。工程与应用科学杂志，13（24），第 10482-10489 页。
[8] P.N. BELHUMEUR，J.P。HESPANHA 和 D.J. KRIEGMAN。（1997）特征脸与渔夫脸：使用类特定线性投影的识别。电气工程师学会模式分析与机器智能交易，19（7），第 711-720 页。

[9] 赵维，CHELLAPPA，R。和 菲利普斯，P.J。（1999）用于人脸识别的子空间线性判别分析。马里兰大学公园市：马里兰大学。
[10] SIROVICH，L. 和 KIRBY，M.（1987）表征人脸的低维程序。美国光学学会杂志一种，4（3），第 519-524 页。
[11] THORAT，S.B.，NAYAK，S.K。和 DANDALE，J.P。（2010）面部识别技术：印度范围内的分析。计算机科学与信息安全学报，8（1）。可从 https://arxiv.org/ftp/arxiv/papers/1005/1005.4263.pdf 获取。
[12] AVEXANDER，D。和 RICHERT-BOE，J。人脸识别技术伦理学。[在线]可从以下网站获得：http://www.ethicapublishing.com/ethics/4CH11.pdf [访问于 14/01/20]。
[13] PANTIC，M。和 ROTHKRANTZ，L.J。（2000）面部表情自动分析：最新技术。电气工程师学会模式分析与机器智能交易，22，第 1424-1445 页。
[14] DAUGMAN，J.（1997）面部和手势识别：概述。电气工程师学会模式分析与机器智能交易，19（7），第 675-676 页。
[15] 赵维，切尔拉帕河，菲利普斯，P.J。和 罗森菲尔德，A。（2003）人脸识别：文献调查。ACM 计算调查，35（4），第 399-458 页。
[16] PUJOL，J.V.，LUMBRERAS，F. 和 VILLANUEVA，J.J.（2001）用于面部编码和识别的拓扑主成分分析。模式识别字母，22，第 769-776 页。
[17] CHELLAPPA，R.，WILSON，C. 和 SIROHEY，S.（1995）人脸与机器的识别：一项调查。电气工程师学会论文集，83（5），第 705-740 页。
[18] KIRBY，M. 和 SIROVICH，L.（1990）卡伦嫩程序在表征人脸中的应用。电气工程师学会模式分析与机器智能交易，12（1），第 103-108 页。
[19] GONG，S.，MCKENNA，S.J. 和 PSARROU，A.（2000）动态视觉：从图像到人脸识别。伦敦：帝国学院出版社。
[20] U. PARK，YONG T. 和 A.K. JAIN（2010）年龄不变的人脸识别。电气工程师学会模式分析与机器智能交易，32（5），第 947-954 页。
[21] LI，X.，MORI，G. 和 ZHANG，H.（2006）带有表情分类的表情不变脸部识别。在：2006 年 6 月在魁北克举行的第三届加拿大计算机和机器人视觉加拿大会议论文集。新泽西州皮斯卡塔维：电气与电子工程师协会。
[22] RIAZ，Z.，MAYER，C.，WIMMER，M.，BEETZ，M. 和 RADIG，B.（2009）一种基于模型的表情不变脸部识别方法。在：M.S. TISTARELLI 和 M.S. NIXON（主编）生物识别技术的进展。工商银行 2009。计算机科学讲义，第 1 卷。 5558。柏林，海德堡：施普林格，第 289-298 页。
[23] MURTAZA，M.，SHARIF，M.，RAZA，M. 和 SHAH，J.H.（2013）不同面部表情下的面部识别分析：一项调查。国际阿拉伯信息技术杂志，10（4），第 378-388 页。
[24] HUANG F.J.，ZHOU Z.，ZHANG，H.-J. 和 CHEN，T.（2000）姿势不变的人脸识别。在：2000 年 3 月，格勒诺布尔，第四届电气工程师学会自动面部和手势识别国际会议论文集。新泽西州，皮斯卡塔维：电气与电子工程师协会。
[25] SHAH，J.H.，SHARIF，M.，RAZA，M。和 AZEEM，A。（2014）跨姿势变化和 3 小号问题的人脸识别。土耳其电气工程与计算机科学学报，22 (6)，第 1423-1436 页。
[26] WEI，X.，LI，C.-T. 和 HU，Y.（2012）在考虑结构稀疏性的不同光照和遮挡下的稳健人脸识别。于：2012 年国际数字图像计算技术和应用国际会议论文集，弗里曼特尔，2012 年 12 月。新泽西州皮斯卡塔维：电气与电子工程师学会。
[27] SHARIF，M.，ANIS，S.，RAZA，M. 和 MOHSIN，S.（2012）增强的基于 SVD 的人脸识别。应用计算机科学与数学学报，12，第 49-53 页。
[28] BISHOP，C.M。（1995）神经网络的模式识别。纽约：牛津大学出版社。

[29] JAIN，A.K.，DUIN，R.P.W. 和 MAO，J.（2000）统计模式识别：综述。电气工程师学会模式分析与机器智能交易，22（1），第 4-37 页。

[30] WU，J. 和 ZHOU，Z.-H.（2002）人脸识别，每人一张训练图像。模式识别字母，23（14），第 1711-1719 页。

[31] PHILLIPS，P.J.，WECHSLER，H.，HUANG，J. 和 RAUSS，P.（1998）费雷特数据库和面部识别算法的评估程序。影像与视觉计算，16（5），第 295-306 页。

[32] MOSSLAH，A.A。（2018）基于投资回报率的远程医疗医学图像压缩（脊柱医学图像案例研究）。全球医药技术杂志。可从 http://www.jgpt.co.in/index.php/jgpt/article/view/811 获得。

[33] LUAIBI，M.K。和 MOHAMMED，F.G.（2019）基于载重吨 –猪–具有 MLP 分类器的 PCA 功能的面部识别。西南交通大学学报，54（6）。可从 http://jsju.org/index.php/journal/article/view/400 获得。

[34] BODRYSHEV，V.V.，ABASHEV，V.M.，KORZHOV，N.P. 和 TARASENKO，O.S.（2018）研究喷射流与超声流在视频帧图像强度参数上的相互作用。佩里科迪科奇奎米卡，特刊 1，第 348-358 页。