Proceedings of TMCE 2020, 11-15 May, 2020, Dublin, Ireland, edited by I. Horváth and G. Keenaghan

EVALUATION OF FACE ANALYSIS METHODS FOR PERSONALIZATION IN DRIVER MONITORING SYSTEMS

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ABSTRACT

Recently, research and development in the topic of driver monitoring systems has become more and more popular. Since self-driving cars remain the long perspective, research & development community in the field of intelligent transportation concentrated on driver monitoring in-vehicle cabin to reduce the number of traffic accidents. The paper presents an analysis of the relevant work and reviews modern methods for identifying potentially distracting driver situations based on the analysis of images received from the front camera of the smartphone. The study aims to answer the question: how to set up methods for analyzing facial images for different types of faces (for example, in Europe or Asia) to personalize the system and increase the accuracy of facial features detection. Progress in the field of deep learning is widely used in modern identification systems and can also be applied to the problem under consideration. The paper assesses the advantages and disadvantages of the existing machine learning methods in relation to the problem under consideration.

KEYWORDS

Face analysis, personification, deep learning, artificial neural networks, convolutional neural networks

1. INTRODUCTION

Research and development in the topic of driver monitoring systems has become popular. In November 2019, the EU announced to make driver monitoring systems mandatory for every vehicle. There are a lot of companies developing hardware and software systems to understand driver drowsiness and distraction [1], [2]. One of the most promising technology for drowsiness and distraction identification is the images of the driver's head position and their analysis. To get these images, it is possible to use a smartphone that tracks the driver's head.

To identify unsafe driving, the classification of hazardous conditions is determined based on the information from the front camera of the smartphone by continuous monitoring of the driver's eyes to recognize drowsiness and image recognition algorithms to recognize the facial features of the driver.

Face recognition is one of the most successful image analysis applications that has garnered significant attention due to availability of feasible technologies, including mobile solutions. The research in the field of facial recognition has been carried out since the 1960s, but the problem has not been completely solved. Advances in modeling techniques and face analysis have brought great changes in this area. Although face detection and tracking systems have been developed, reliable face recognition technology remains a major challenge for researchers in computer identification and modeling. There are many reasons for the increasing interest in face recognition, including security issues, identity verification needs in the digital world, face analysis and modeling techniques in multimedia data management and computer entertainment. In the early 1990s and 2000s, the study of face recognition became popular with the major technical streams, such as linear subspace, manifold, and sparse representation. However, these methods do not solve the problem of angle change and face direction . In the early 2010s, learning-based local descriptions were introduced to the facial recognition community, where local filters were studied to better differentiate and make programming short.

Although the research community has presented improvements in pre-treatment, local description, and feature transitions, these methods have slowly improved face recognition accuracy. The majority of methods are aimed at dealing with facial changes in a certain aspect, such as lighting, posture, expression or disguise with no integrated technique to address these unlimited challenges holistically.

The situation changed in 2012 when AlexNet presented a deep learning technique. Deep learning methods, such as convolutional neural networks, use a cascade of multiple layers of processing units for feature extraction and transformation. Deep convolutional neural networks (CNN) with the initial layers automatically learn the features designed for years or even decades, such as Gabor and SIFT, and the later layers learn higher-level abstraction. Finally, the combination of these higher-level abstraction represents facial identity with unprecedented stability.

The paper discusses the advantages and disadvantages of the current face analysis methods, followed by discussions about technical issues and issues of racial and gender factors. Based on the results presented, appropriate algorithms that can be used for facial expression recognition on driver face in different context situations are defined.

To determine unsafe driving, we need to analyze and identify each object on the driver's face (eyes, nose, mouth, ears) to obtain accurate results of the driving situation, for example: to determine if the eyes are closed or open, looking straight or sideways, blinking eye speed fast or slow, mouth yawning or not [3], [4].

The input is a camera image aimed at the driver. The methods to detect and identify faces and other parts of the face, such as the eyes, nose, mouth, ears are presented. Each part is tracked and analyzed, and a warning signal is given in advance when signs of fatigue or drowsiness appear.

The classification of hazardous conditions is determined based on information from the front camera of the smartphone and the sensor. The camera can be used to constantly monitor the driver's eyes condition, detect drowsiness or use image recognition algorithms to recognize driver's facial features and warn them with an audio signal.

Face images from the front camera are collected and analyzed to determine the calculated parameters such as open eyes, yawn, open mouth and pitch angle. Therefore, this paper analyses methods for identifying face parts from the front camera image to determine the calculated parameters, such as eye opening, yawning angle, head tilt, and open mouth (Figure 1). The article discusses the advantages and disadvantages of popular methods for face detection, such as facial features, position of the eyes, nose and other parts of the body, as well as technical and factor problems. Race and gender, such as differences in Asian and European eye shape s, facial features and face shapes for personification are presented.

This paper is structured as follows. Section II describes the works related to the topic of face analysis, comparing the advantages and disadvantages of the methods considered, thereby pointing out and discussing technical issues, requirement and specifications to personalize face analysis. Section III presents the results of the experiments with European and Asian face images. The conclusion summarizes the paper.

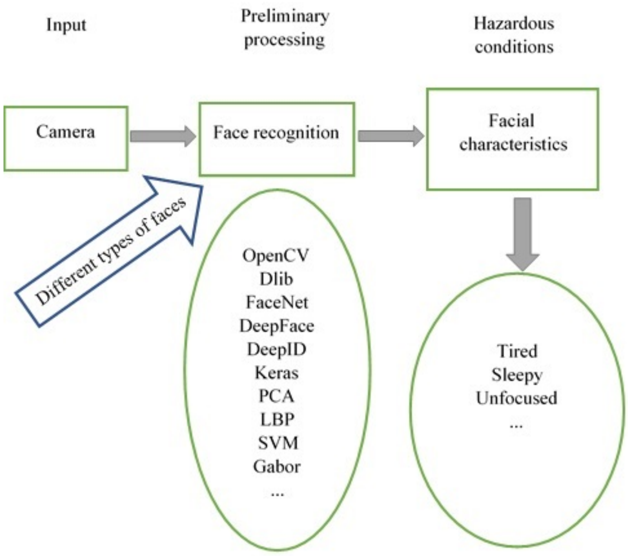

Figure 1 A model for using smartphone data to detect dangerous conditions.

2. RELATED WORKS

2.1. Background

Face analysis technology has been thoroughly researched. Such worldwide known platforms as OpenCV and DLib provide a comprehensive instrument for object identification in the human face. The basics of face analysis are given and solved. Algorithms and methods of identification are divided into large groups: traditional methods, recognition algorithms, artificial neural networks, Gabor wavelets, face descriptor-based methods, 3D-based face analysis methods. The issues with face detection include posture difference, head position, head movement, light, blinking speed have been effectively discussed and solved.

There are several studies on face analysis and personalization. Each study has its own points, referring to each specific problem. As there have not been many studies comparing the theories about personal face analysis with each other, we have visualized the related papers into the chart (see Fig. 1) Recognition here means identifying or verifying a person by comparing and analyzing patterns based on person's facial contours. Personification means simulating the way of a person or animal facial recognition.

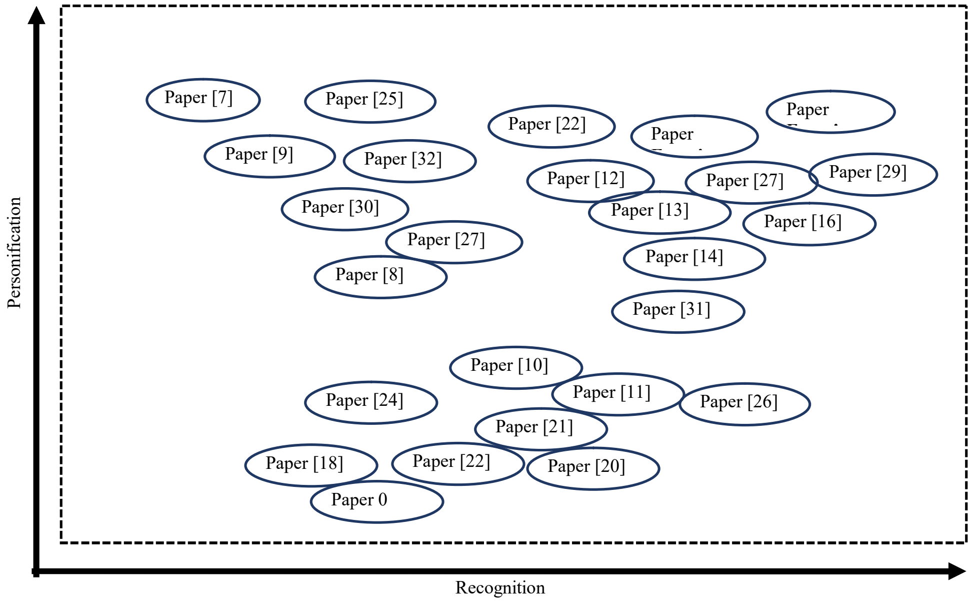

Figure 2 Face analysis paper analysis based on two scales: recognition and personification

2.2. Paper description

The problem of identification of familiar or strange faces is not discussed in [5]. The paper only identifies a group of 5 factors that strongly influence the identification process: lip thickness, eye color, eye shape, eyebrow thickness and 5 other factors that have minor impact on facial recognition results. For white male faces, the eye color and hair color characteristics are important to be distinguished, but not for Asian or African faces. The characteristics of the hair and eyebrow thickness are not used to distinguish infant faces because all faces look very similar.

Face sketches (redrawn images) in 0 are identified by components-based recognition (CBR). . There are 66 facial points in both the sketch and the photo dividing the face into components to locate 5 important components of the face: hair, eyebrows, eyes, nose, and mouth.

Paper [7] refers to the person's position and their looking at the other person's face . The eyes impact in the identification process is influenced by culture, using the Hidden Markov model (HMM). During face recognition process when we look at human faces, our fixed parts are not distributed randomly across the entire face. Different facial areas receive different levels of attention, with eyes, nose, and mouth being the most frequently focused facial features.

Identification issues, differences in positions and positions are also discussed in [8]. In this review, facial recognition techniques through posture are classified into three categories, ie, general algorithms, 2D techniques, and 3D methods. The Eigenfaces method seems to be a fast, simple and practical method, which has become the most widely used face analysis technique. However, it does not provide invariants for posture and rate changes.

A facial recognition algorithm that supports probability geometry to handle posture variations was proposed. In this algorithm, the human head is roughly approximated as an ellipse with a radius, position, and orientation estimated based on the universal mosaic pattern. Later, the image was deformed on the surface of the ellipsoid without changing posture.

Paper [9] refers to the effect of winking in the face recognition algorithm. The face recognition algorithm being tested is a merger of Principal Component Analysis (PCA), extracting features based on local binary patterns (LBP) and support-based classification (SVM). The purpose of the study is not to enhance the operation of the facial recognition algorithm, but to test blinking.

The methods currently used in face recognition, as the Infrared Spectrum (IRS) method to identify faces, are discussed in [10] . The Principal Component Analysis method (PCA) is presented in [11]. It consists of 4 steps: Face positioning and image preprocessing; standard PCA decomposition; Local PCA (LRPCA), a sophisticated PCA implementation; The final step is to re-evaluate the values in the result vector to emphasize the more discriminatory features. The proposed alternative transformations include Gabor wavelengths, local binary patterns, correlation filters, and Grassmann manifolds.

The method of recognizing by Local binary patterns (LBP) is mentioned in [12]. Here, the face image is divided into a set of areas. Local binary feature distribution tables are extracted from these sets, then the tables are merged into an advanced feature vector as a face description. The results clearly show that face images can be viewed as a micro-model component s, such as planes, spots, lines and edges, and can be well described by LBP.

The paper [13] is aimed at facial features detection (eye, mouth, eye center and oral corner positioning) based on geometric information using distance vector fields. Face detection is performed using skin color segmentation in YIQ color space, - used in video systems, followed by fine-tuning steps based on genetic algorithms.

In [14] an algorithm sequence with the ability to identify faces with higher accuracy than some advanced methods including combining SVM, PCA, LBP and neural networks are proposed. The SVM-based classification on LBP operators and PCA-based feature extraction provide higher accuracy compared to Feed Forward Back Propagation Neural Network (FFBPNN) -based classification, keeping the model extracting features change. In addition, in case of SVM, 3D face images result in better classification, due to the ability of 3D images to retain information.

The varying accuracy of face recognition across race and gender has attracted extensive media attention. In paper [15], [16], the false match rate (FMR) and false non-match rate (FNMR) curves plot the false match rate and false non-match rate, respectively, as a function of the decision threshold on the similarity value produced by the matcher. There is a similar qualitative difference between demographic groups: at a given decision threshold, African-Americans have a higher FMR while the Caucasians have a higher FNMR. They have also shown that the gender-based variation in face recognition accuracy is a different phenomenon in terms of how the imposter and genuine distributions differ between men and women. At a fixed decision threshold, women appear to have both a higher FMR and a higher FNMR than men.

In [17] the experiments were conducted to determine the influence of gender and age on the results of identification. The results show that male face recognition accuracy is higher than that of the female, but the male subjects' analysis of the specificity is lower than that of the female.

The reason for this result may be that male facial features are significantly clearer than women, and due to makeup and other factors. so, the recognition rate is better for men than for women the effect of age on men is much higher than that of women. The reason for this may be that young men and older men pay more attention to their appearance, so the facial features of young men and older men are more obvious, but middle-aged men ignore appearances for various reasons. Therefore, characteristics converge and personal characteristics are masked. No matter what age group, women are more concerned about their appearance, so the recognition results do not fluctuate with age.

2.3. Research Comparison

There has been a rapid development of reliable face analysis algorithms over the past decades. Face analysis methods can be divided into several groups: Traditional recognition algorithms, Artificial neural networks, Gabor wavelets, Face descriptor-based methods and 3D - based face analysis. The advantages and disadvantages of each method are shown in Table 1.

Table 1 Face analysis methods overview

#	Method	Advantages	Disadvantages
1	Traditional recognition algorithms [18], [19], [20], [21], [22], [23], [24], [25], [26]	Traditional methods (geometry-based, holistic, feature-based and hybrid methods) based on hand-crafted features are focused on the local structure of the manifold. They project face onto the linear subspace spanned by the eigenface images. The distance from face space is orthogonal to the plane of the mean image and can be easily turned to Mahalanobis distances with a probabilistic interpretation.	These methods may fail to adequately represent faces when large variations in illumination facial expressions and other factors occur. Locally linear embedding (LLE), Locality preserving projection (LPP) and local binary patterns (LBP) brought a simple and effective way to describe neighboring changes in face description. Subspace approaches were applied in Discriminant common vectors (DCV)- and support vector machine (SVM)-based methods. Preserving the local structure between samples is the domain of Neighbourhood preserving projection (NPP) and Orthogonal neighborhood preserving projection (ONPP) methods. The problem is that it is still unclear how to select the neighborhood size or assign optimal values for them.
2	Artificial neural networks [4], [24], [25], [27], [28]	Radial-basis functional artificial neural network is naturally integrated with non-negative matrix factorization. Other approaches for process simplification regarding ANNs native linearisation feature and computation speed up are used. Artificial neural networks are an ideal solution, especially for recognizing face images with partial distortion and occlusion.	The main disadvantage of this approach is the requirement of a greater number of training samples (instead of one or a limited number). It is inaccurate in the same way as other statistically based methods.
3	Gabor wavelets [28], [29]	The Gabor wavelets exhibit desirable characteristics of capturing salient visual properties like spatial localization orientation selectivity and spatial frequency. Different biometrics applications favor this approach.	The drawback of the Gabor-based methods is the significantly high dimensionality of the Gabor feature space since face image is convolved with a bank of Gabor filters. The approach is computationally intensive and impractical for real-time applications. Additionally, simplified Gabor features are sensitive to lighting variations.

4	Face descriptor-based methods [5], [16], [24],	The main idea behind the developing image descriptors is to learn the most discriminant local features that minimize the difference between images of the same individual and maximize that between images from the other people. These methods are discriminative and robust to illumination and expression changes. They offer compact, easy to extract and highly discriminative descriptors.	The approach is computationally intensive during the descriptor extraction stage but encourages simplicity and performance in reference to online applications.
5	3D-based face analysis [30], [31]	Extends the traditional 2D capturing process and has greater potential for accuracy. The depth information does not depend on the pose and illumination making solution more robust	Requires all the elements of the 3D face analysis system to be well-calibrated and synchronized to existing 3D data. Computationally expensive and not suitable for practical applications.

2.4. Requirements Specification

From the above-mentioned comparisons of popular facial recognition methods, we see the success of deep learning systems that combine artificial neural networks. Deep Neural Networks (DNNs) have established themselves as a dominant technique in machine learning. Convolutional neural networks (CNNs) have been used in nearly all top-performing methods on the Labeled Faces in the Wild (LFW) dataset [4]. It is the most effective and advanced solution in personal face analysis technology. Despite important success, this solution still faces problems leading to reduced performance. Therefore, in order to solve these problems gradually, requirements or r factors that effectively limit and help improve the accuracy and speed of facial recognition technology in the future are to be discussed:

- **Image quality:** Image quality affects how well facial-recognition algorithms work. The image quality of the scanning video is quite low compared with that of a digital camera. Even high-definition video is, at best, 1080p (progressive scan); usually, it is 720p. These values are equivalent to about 2MP and 0.9MP, respectively, while an inexpensive digital camera attains 15MP. The difference is quite noticeable. Therefore, the research to improve image quality and extract good quality front images from low-resolution video sequences is being studied and actively supports face analysis technology.

- **Image size**: When a face-detection algorithm finds a face in an image or in a still video frame, the relative size of that face compared with the enrolled image size affects how well the face is recognized. An already small image size, coupled with a target distance from the camera, means that the detected face is only 100 to 200 pixels on aside. Further, having to scan an image for varying face sizes is a processor-intensive activity. Most algorithms allow the specification of a face size range to help eliminate false positives on the detection and speed up image processing. An additional combination of methods to analyze local or interpolated images is an essential option.

- **Face angle:** The relative angle of the target's face influences the recognition score profoundly. When a face is enrolled in the recognition software, usually multiple angles are used (profile, frontal and 45-degrees are common). Anything less than a frontal view affects the algorithm's capability to generate a template for the face. The more direct the image (both enrolled and probe image) and the higher its resolution, the higher the score of any resulting matches. The combination of 3D identification solutions and bulk data is a good solution to this problem.

- **Processing and storage:** Even though the high-definition video is quite low in resolution when compared with digital camera images, it still occupies significant amounts of disk space. Processing every video frame is hard, so usually, only a fraction (10 to 25 percent) is actually run through a recognition system. To minimize the total processing time, agencies can use computer clusters. However, clustering involves considerable data transfer over a network, which can be bound by input-output restrictions, further limiting processing speed.

To analyze big amount of data, a computer is better than a human, as a human cannot process big data quickly and qualitatively. Humans can only look for a few individuals at a time when watching a source video. A computer can compare many individuals against a database of thousands. As technology improves, higher-definition cameras become available. Computer networks are able to move more data, and processors work faster. Facial-recognition algorithms are better able to pick out faces from an image and recognize them in a database of the enrolled individuals. The simple mechanisms that defeat today's algorithms, such as obscuring parts of the face with sunglasses and masks or changing one's hairstyle, can be easily overcome. An immediate way to overcome many of these limitations is to change the way images are captured. Using checkpoints, for example, requires subjects to line up and funnel through a single point. Cameras can then focus on each person closely, yielding far more useful frontal, higher-resolution probe images. However, wide-scale implementation increases the number of cameras required.

- Data for training: A Deep neural network (DNN) has established itself as a dominant technique in machine learning. DNN is the top performer in many tasks including image classification and face analysis. Combined neural networks (CNN) are used in nearly all top-performing methods on data sets labeled in wild faces (LFW). When there is enough data for the training process, these systems are capable of in-depth analysis, solving the most difficult problems that other methods still entail. This is the focus future technology needs to address. However, all these methods emphasize the need for both a larger and more challenging public data set to evaluate these systems. Deep neural networks require large amounts of data, preferably tens of millions of images. Therefore, individual datasets simply do not have enough data for modern deep learning systems to train. The inevitable tendency of the community is to resonate and contribute to a shared data set to solve problems more effectively.

- Lack of variety and poor generalization: Previous generation datasets like The Yale Face Database [2] were captured under highly controlled laboratory environments. Datasets such as LFW and Cross-Age Celebrity Dataset (CACD) [33] claim to be "in the wild" but are taken almost exclusively by professional photographers with Digital single-lens reflex cameras (DSLR) in well-lit environments. Training on such datasets will likely lead to poor generalization errors when the models are confronted with a less constrained operating environment such as a photostream from a mobile phone or a low-quality camera.

3. METHODS OF EVALUATION

To answer the question on how to adapt face analysis methods for different kinds of faces (e.g., European or Asian) to enrich personalization during the face analysis process, the traditional recognition algorithms and artificial neural network (see (1) and (2) in the Table 1) have been evaluated.

A dataset that contains 100 images, 50 Asian faces and 50 European ones, including 25 images of full faces, and 25 images of turned faces was formed. Pictures were taken from accessible datasets, preliminary results were obtained, and the main features of the methods analyzed were determined. Next, experiments on a large sample are planned. We implemented tests using the traditional recognition algorithms approach and artificial neural network and measured the face analysis performance (see Table 2) and face analysis accuracy (see Table 3). Results show that artificial neural networks process the images more slowly but with a higher level of accuracy. Also, the European faces are determined slower than Asians.

Table 2 Performance comparison

Face	Traditional recognition algorithms (time, sec)	Artificial Neural Network (time, sec)
Asian full	0,039	0,095
Asian turned	0,035	0,088
European full	0,042	0,091
European turned	0,035	0,094

The accuracy of European face and eye determination is higher than that of Asians in both algorithmic groups. Due to the peculiarities of the eye structure of the Asian, the aperture is often smaller than that of Europeans. Eye characteristics are often less obvious; therefore, the exact detection rate for European people is often higher than that of Asians.

4. CONCLUSION

The paper presents the results of object detection on

Table 3 Accuracy comparison

Face	Traditional recognition algorithms (accuracy, %)	Artificial Neural Network (accuracy, %)
Asian full	40	80
Asian turned	24	92
European full	56	100
European turned	40	92

face and specification requirements for facial recognition and personification of recognition systems. Deep learning has been integrated into most modern face detection models and methods. This change has led to a large increase in the accuracy of face analysis systems and has formed the current online standard for face analysis, LFW and saturation. The deep learning models combined with neurons have made remarkable achievements, greatly improving the accuracy and speed of execution. The degree of dependence and human impact on the system is decreasing. Systems gradually become smart and achieve the same performance as humans. Currently, there are many face data sets of different organizations, both public and private, that can be used to research visual recognition methods. Data requirements for deep networks highlight the need for a new, very large- scale data (tens of millions of images) and publicity to research face analysis.

ACKNOWLEDGMENTS

The research is funded by the Russian Science Foundation (project # 18-71-10065).

REFERENCES

[1] Regulation (EU) 2019/2144 of the European Parliament and of the Council of 27 November 2019; https://ec.europa.eu/growth/sectors/automotive/safety_en.

[2] Yale face database (n.d.). Retrieved March 10, 2003, from http://cvc.yale.edu/projects/yalefaces/yalefaces.html.

[3] Kashevnik, A., Lashkov, I., & Gurtov, A. (2019). Methodology and Mobile Application for Driver Behavior Analysis and Accident Prevention. IEEE Transactions on Intelligent Transportation Systems.

[4] Balaban, S. (2015, May). Deep learning and face recognition: The state of the art. In Biometric and Surveillance Technology for Human and Activity Identification XII (Vol. 9457, p. 94570B). International Society for Optics and Photonics.

[5] Abudarham, N., Shkiller, L., & Yovel, G. (2019). Critical features for face recognition. Cognition, 182, 73-83.

[6] Liu, D., Li, J., Wang, N., Peng, C., & Gao, X. (2018). Composite components-based face sketch recognition. Neurocomputing, 302, 46-54.

[7] Chuk, T., Crookes, K., Hayward, W. G., Chan, A. B., & Hsiao, J. H. (2017). Hidden Markov model analysis reveals the advantage of analytic eye movement patterns in face recognition across cultures. Cognition, 169, 102-117.

[8] Zhang, X., & Gao, Y. (2009). Face recognition across pose: A review. Pattern Recognition, 42(11), 2876-2896.

[9] Shankar, S. (2015, June). Assessment of the effect of variations in Eye Blinks on a face recognition algorithm. In 2015 IEEE International Advance Computing Conference (IACC) (pp. 371-376). IEEE.

[10] Singh, S., & Prasad, S. V. A. V. (2018). Techniques and Challenges of Face Recognition: A Critical Review. Procedia computer science, 143, 536-543.

[11] Givens, G. H., Beveridge, J. R., Phillips, P. J., Draper, B., Lui, Y. M., & Bolme, D. (2013). Introduction to face recognition and evaluation of algorithm performance. Computational Statistics & Data Analysis, 67, 236-247.

[12] Ahonen, T., Hadid, A., & Pietikainen, M. (2006). Face description with local binary patterns: Application to face recognition. IEEE transactions on pattern analysis and machine intelligence, 28(12), 2037-2041.

[13] Asteriadis, S., Nikolaidis, N., & Pitas, I. (2009). Facial feature detection using distance vector fields. Pattern Recognition, 42(7), 1388-1398.

[14] Shankar, S., & Udupi, V. R. (2016). Recognition of Faces-An Optimized Algorithmic Chain. Procedia Computer Science, 89, 597-606.

[15] Bowyer, K. (2019). Why face recognition accuracy varies due to race. Biometric Technology Today, 2019(8), 8-11.

[16] Chen, J., Shan, S., He, C., Zhao, G., Pietikainen, M., Chen, X., & Gao, W. (2009). WLD: A robust local image descriptor. IEEE transactions on pattern analysis and machine intelligence, 32(9), 1705-1720.

[17] Wang, D. (2019). Effect of subject's age and gender on face recognition results. Journal of Visual Communication and Image Representation, 60, 116-122.

[18] Turk, M., & Pentland, A. (1991). Eigenfaces for recognition. Journal of cognitive neuroscience, 3(1), 71-86.

[19] Bartlett, M. S., Movellan, J. R., & Sejnowski, T. J. (2002). Face recognition by independent component analysis. IEEE Transactions on neural networks, 13(6), 1450-1464.

[20] Belhumeur, P. N., Hespanha, J. P., & Kriegman, D. J. (1997). Eigenfaces vs. fisherfaces: Recognition using class specific linear projection. IEEE Transactions on pattern analysis and machine intelligence, 19(7), 711-720.

[21] Hu, H., Zhang, P., & De la Torre, F. (2010). Face recognition using enhanced linear discriminant analysis. IET computer vision, 4(3), 195-208.

[22] Yang, J., Zhang, D., Frangi, A. F., & Yang, J. Y. (2004). Two-dimensional PCA: a new approach to appearance-based face representation and recognition. IEEE transactions on pattern analysis and machine intelligence, 26(1), 131-137.

[23] Naseem, I., Togneri, R., & Bennamoun, M. (2010). Linear regression for face recognition. IEEE transactions on pattern analysis and machine intelligence, 32(11), 2106-2112.

[24] Lu, J., Plataniotis, K. N., & Venetsanopoulos, A. N. (2003). Face recognition using kernel direct discriminant analysis algorithms. IEEE Transactions on Neural Networks, 14(1), 117-126.

[25] He, X., Yan, S., Hu, Y., Niyogi, P., & Zhang, H. J. (2005). Face recognition using laplacianfaces. IEEE transactions on pattern analysis and machine intelligence, 27(3), 328-340.

[26] Poh, N., Chan, C. H., Kittler, J., Marcel, S., Mc Cool, C., Rúa, E. A., ... & Pavesic, N. (2010). An evaluation of video-to-video face verification. IEEE Transactions on Information Forensics and Security, 5(4), 781-801.

[27] Zhang, B. L., Zhang, H., & Ge, S. S. (2004). Face recognition by applying wavelet subband representation and kernel associative memory. IEEE Transactions on neural networks, 15(1), 166-177.

[28] Trigueros, D. S., Meng, L., & Hartnett, M. (2018). Face recognition: from traditional to deep learning methods. arXiv preprint arXiv:1811.00116.

[29] Serrano, Á., de Diego, I. M., Conde, C., & Cabello, E. (2010). Recent advances in face biometrics with Gabor wavelets: A review. Pattern Recognition Letters, 31(5), 372-381.

[30] Kemelmacher-Shlizerman, I., & Basri, R. (2010). 3D face reconstruction from a single image using a single reference face shape. IEEE transactions on pattern analysis and machine intelligence, 33(2), 394-405.

[31] Bowyer, K. W., Chang, K., & Flynn, P. (2006). A survey of approaches and challenges in 3D and multi-modal 3D+ 2D face recognition. Computer vision and image understanding, 101(1), 1-15.

[32] Jabid, T., Kabir, M. H., & Chae, O. (2010, September). Facial expression recognition using local directional pattern (LDP). In 2010 IEEE International Conference on Image Processing (pp. 1605-1608). IEEE.

[33] Cross-Age Reference Coding for Age-Invariant Face Recognition and Retrieval https://bcsiriuschen.github.io/CARC/