Global Facial Recognition Using Gabor Wavelet, Support Vector Machines and 3D Face Models

Jos é Augusto Cadena Moreano and Nora Bertha La Serna Palomino National University of San Marcos, Lima, Peru Email: {jose.cadena, nlasernap}@unmsm.edu.pe

Abstract-The present research is aimed to develop an optimal method for face recognition based on wavelet Gabor filtering, feature extraction, and Support Vector Machine (SVM) using the BU-3DFE database containing 3D face models. Process for working with 350 models corresponding to 50 persons, i.e. 10 models per person divided seven for training and three for testing. The proposed technique involves projecting the face models obtained from the BU-3DFE database to the three planes using Matlab 2015a functions, and then, treating them as 2D images for recognition. The aim of this work is to achieve efficient 3D facial recognition with acceptable performance. As a result, the highest obtained value was 97.3% for SVM (kernel cubical). The results obtained for the proposed approach were compared with those of other recent 3D facial recognition methods to evaluate the potential of the former. Contribution of the present research is to facilitate urban security through providing a more efficient way for recognition of people who threaten the peace and tranquility of society, public or private institution, etc.

Index Terms—databases, support vector machine, facial recognition, Gabor, feature extraction

I. INTRODUCTION

A Facial Recognition System (FRS) is an application managed by an electronic system that is aimed to automatically identify a person using a digital device. Currently, several concepts related to facial recognition, such as handling [1], consider FRS as a process that, given one or more images of an unknown face selected from the range of faces registered in a database, returns the identity of the face in question with a greater degree of similarity or dissimilarity. Another related study presented in [2] considers facial recognition as a process of extracting characteristics that can be treated as local, global, and mixed. The key issue of facial recognition is related to the part of interaction between people and computers that in turn has become a separate discipline [3] referred to as Human Computer Interaction (HCI). It is aimed to investigate and address all aspects related to design and implementation of interfaces between humans and computers.

One of the most important classifiers used in RFS processes is the Support Vector Machine (SVM) introduced by Vapnik [4]. SVM is a pattern classifier that, given a set of classes, constructs a hyperplane or a set of hyperplanes to separate these classes into a very high (or even infinite) spatial dimensionality that can be used to solve classification or regression problems. SVM is employed efficiently as a training system for linear learning machines with many classification and regression applications, such as image classification, character recognition, protein detection, pattern classification, function identification, and others [5]. One of the way to perform facial recognition is to match characteristics of the image search with a trained classifier. With regard to this approach, numerous classification methods, such as deep neural networks, Bayesian classifier, and SVM, have been applied to identify faces [6].

SVM classification is performed by identifying a hyperplane that separates different classes. The hyperplane needs to be defined in such way to separate the maximum distance between the nearest sample (each class) and the hyperplane classes; this distance is denoted as margin [7]. Currently, there are a variety of available 3D databases. However, there is a deficiency associated with high economic cost of obtaining the access to these databases. Nevertheless, there are several laboratories that provide the access to similar databases for research purposes. One of them is the Department of Computer Science, Binghamton State University of New York [8] possessing the face image database BU-3DFE that has been employed in the present study.

Facial recognition is a biometric method that has a wide range of applications in today's technological world, specifically, with regard to security. The process of facial recognition can be applied in many aspects of daily life, such as, for example, identifying a person who opens the cash register in an attempted robbery or in a small supermarket; and in an extreme case, it can be applied at ATMs for validation purposes instead of current ATM cards. Moreover, it can be applied on a smaller scale to the access systems used in companies, universities, etc. In addition, it can be used in various applications, such as recognition of friends in social networks, identification on a cell phone, computer, or tablet, granting access to ATMs, and others. On a large scale, it could be implemented at a side of police authorities to locate persons who have

Manuscript received January 17, 2020; revised May 15, 2020.

committed serious damage to society, including such applications as passport control, street safety, stadiums, airports, etc.

Currently, researchers seek to develop the systems to address problems of certain environment conditions, such as lighting, age, rotation, translation, depth, facial expressions, occlusions, hair, and others. Related studies also aim to determine the most effective technique for facial recognition based on the results of investigating the main research trends in this field.

The present research is aimed to develop a 3D facial recognition tool using SVM, which has certain characteristics that are advantageous comparing to other popular classification techniques. The most notable differences between SVM and other similar algorithms are application of a new inductive principle, which seeks to minimize the structural risk, as well as the use of the central or core function to provide larger capacity for generalization, even when a training dataset is small. Another characteristic that is worth mentioning is that the concept of SVM belongs to machine learning or statistical learning disciplines, where the main idea is to make machines learn.

The main contribution of the present research work is to facilitate urban security through introducing a more efficient application for recognition of people who threaten the peace and tranquility of society, public or private institution, etc.

To sum up, in the present paper, we firstly present a new methodology, then we describe the setup for the conducted experiment and the obtained results together with the respective analysis. Finally, we make the conclusions on the results of the conducted experiment and comparison between the proposed method and alternative ones.

II. METHODOLOGY

In 3D facial recognition, we design a model divided into two stages: training and testing that start from selection of the same database to perform the validation process (recognition). The model is established according to the scheme presented in Fig. 1.



Figure 1. The model established for global 3D facial recognition.

A. Database

It the present study, we work with the database BU-3DFE [8] containing 2500 image models, which correspond to 100 people, i.e. 25 models per person in *.wrl format with characteristics of face expression and gender. In the considered dataset, 56% of image models corresponded to men, and 46% to women, aged from 18 to 70. A part of this database is presented in Fig. 2.

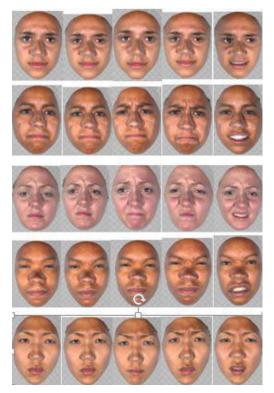


Figure 2. Database BU-3DFE.

In the present study, we identified a testing set of 50 people, where each person had seven 3D face models for training and three ones for testing with different expressions, intensity levels, and gender, providing a total of 500 models.

B. Projection of a Flat Face

At the next step, using the projection algorithm applied to the planes available as an eigenfunction in Matlab 2015a [12]-[14], we projected each face model to the three planes (x-z), (y-z), and (z-x). A part of the obtained results is presented in Fig. 3.

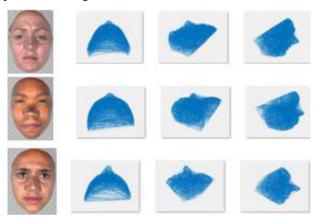


Figure 3. Projection of 3D model planes (x-z), (y-z), and (z-x).

C. Feature Extraction by Wavelet Gabor

Feature extraction is applied to perform transformation of the original features to generate other more meaningful features [9]. So far, the most common way to analyze the periodic properties of textures to perform processing using the bank of special filters referred to as the Gabor filters, which are bandpass filters providing information on spatial frequencies related to images and their orientation. According to Mari ñas [10], each spectra of a Gabor filter is defined by three parameters:

- 1) The center frequency, which is highlighted if a texture has significant spatial frequency components.
- 2) Scaling which is used to pass frequencies around the center frequency.
- 3) Orientation, which implies that in the domain of images (two-dimensional), frequencies are defined as vectors with the magnitude and phase. For example, phases or orientations may be used to distinguish between horizontal and vertical stripes corresponding to the same frequency.

According to Mariñas [10], to extract texture features from a bank, four filters are used being often spaced as possible to provide maximum coverage of the spectrum. These filters are represented in the frequency domain, and it can be seen how the bandwidth of each filter increases with frequency. Lower frequencies are not covered, because they do not express the sufficient amount of information about the image (only the average level of illumination). The feature extraction process involves filtering each image by each of the four filters and then, measuring each filter response to a particular image. In this method, the mean absolute deviation is calculated for each filtered image as per Equation (1):

$$f = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} |x_{i,j} - \bar{x}|$$
(1)

where x is the average of the filtered image, M and N are dimensions, and **f** is calculated for each filtered image to provide four rotation invariant features. Similarly, Sujitha in [6] considers that Gabor wavelet can be successfully applied for feature extraction considering the properties of discrimination, such as scale and orientation. This process implies that the characteristics of the Gabor-collected faces are provided using the input grayscale. The spatial domain of the Gabor filter 2D Gaussian function is a core modulated by a sine wave. Gabor wavelet filters can be applied to various problems, such as detection and feature extraction, owing to their properties.

The regular function of a two-dimensional Gabor wavelet can be described in the spatial frequency domain [6]. It is given as per Equation (2):

$$g(x, y) = \exp\left[\frac{x^2 + y^2}{2\sigma_{xy}^2}\right] \cos(u_0 x + v_0 y)$$
(2)

where σ_{xy} is standard deviation of the Gaussian coverage representing the extent of the spatial domain and the

transmission capacity of the Gaussian filter. Parameters (u_0 , v_0) characterize the spatial frequency of the sinusoidal curve, which is represented in two-dimensional coordinates as r0 and θ frequency radial orientation. It is defined as per Equation (3):

$$r_0^2 = u_0^2 + v_0^2$$
, $\tan \theta = \frac{v_0}{u_0}$ (3)

The density and angular discriminatory characteristics of Gabor wavelets are more accurate in their representation of a density range showing the amount by which the Gaussian filter changes each component density of an input image. In most applications, Gabor wavelets are used with five scales, U = 5, and eight orientations, V = 8, thereby providing a complete set of Gabor wavelets equal to 40 [11]. Fig. 4 shows the magnitude corresponding to five scales, and the real parts obtained with five scales and eight orientations.

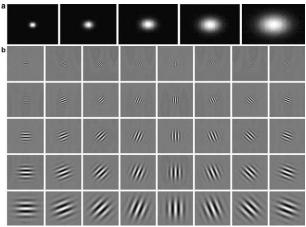


Figure 4. The Gabor wavelet assembly of 40. (a) The magnitude of the five scales. (b) The real parts corresponding to the eight orientations and five scales.

The revised algorithm is based on the selected Gabor wavelet to filter and extract features of the obtained 2D projections. This algorithm has been chosen, as it allows achieving good results, as outlined in several related studies.

D. Vector Features

Defining vector features implies the process in which all major features extracted at the previous step are stored in vectors. A portion of vector features is shown in Fig. 5.

	1	2	3	4	5	6	7	8	9	10	11	12	13
5	0.7489	1.9145	-0.6735	-0.6601	-0.6487	-0.6810	2.1832	0.0292	-0.5172	-0.5018	-0.5715	-0.6220	2.2325
6	0.7580	1.9095	-0.6823	-0.6590	-0.6566	-0.6696	2.1662	0.1072	-0.6025	-0.5653	-0.5182	-0.5873	2.2290
7	0.7600	1.9084	-0.6741	-0.6503	-0.6685	-0.6755	2.1564	0.1437	-0.6072	-0.5056	-0.5813	-0.6060	2.235;
8	0.7672	1.9044	-0.6700	-0.6600	-0.6660	-0.6757	2.1171	0.2812	-0.6014	-0.5791	-0.5927	-0.6250	2.214
9	0.7442	1.9170	-0.6754	-0.6406	-0.6674	-0.6778	2.1760	0.0680	-0.5876	-0.5431	-0.5427	-0.5707	2.2354
10	0.7237	1.9282	-0.6691	-0.6556	-0.6643	-0.6629	2.1659	0.1101	-0.5752	-0.5362	-0.5714	-0.5932	2.2313
11	0.7412	1.9187	-0.6730	-0.6502	-0.6662	-0.6705	2.1645	0.1168	-0.5736	-0.5632	-0.5819	-0.5627	2.236(
12	0.8295	1.8683	-0.6746	-0.6440	-0.7048	-0.6744	2.1967	-0.0415	-0.4610	-0.5623	-0.6068	-0.5252	2.1838
13	1.3467	1.4796	-0.7021	-0.7009	-0.7166	-0.7066	2.2285	-0.2762	-0.4968	-0.4358	-0.4906	-0.5292	2.235
14	1.3162	1.5078	-0.7039	-0.6974	-0.7181	-0.7047	2.2176	-0.1764	-0.5413	-0.4275	-0.5487	-0.5238	2.2355
15	1.2973	1.5248	-0.7209	-0.6986	-0.7175	-0.6851	2.2323	-0.3290	-0.4691	-0.4416	-0.5152	-0.4774	2.2348
16	1.7812	0.9678	-0.6670	-0.7083	-0.6737	-0.7001	2.2211	-0.1987	-0.4467	-0.5235	-0.5250	-0.5272	2.235: \

Figure 5. Vector characteristics obtained from the bank of Gabor filters.

E. Classification

Classification is applied to allocate different parts of the feature vector groups or classes based on the features

extracted at the previous steps. The process is performed both for training images (learning) and testing. In the present study, we employed SVM as a classifier using its kernels: linear, cubic, and Gaussian.

F. Validation (Recognition)

Validation was performed to check whether a test image corresponds to a particular class. This allowed concluding on whether the identification result was correct or misguided.

III. RESULTS

In the present study, the face recognition process was divided into the two parts: training and testing. Training was performed using the three projections of each model providing a total of 1050 projections per kernel. The proposed models were trained on these data providing different results for the linear, cubic, and Gaussian kernels as follows: 87.3%, 98.0%, and 94.3%, respectively. The corresponding results are presented in Fig. 6, Fig. 7, and Fig. 8, respectively.



Figure 6. Linear kernel training with the rate of recognition of 87.3%



Figure 7. Cubic kernel training with the rate of recognition of 98%.



Figure 8. Gaussian Kernel training with the rate of recognition of 94.2%.

At the testing stage, as presented in Table I, the proposed approach was tested on 150 models for each kernel providing the following results: 130 correct estimates and 20 errors observed for the linear kernel, in addition to a total of 146 hits; five errors for the cubic kernel and a total of 135 hits, and 15 errors for the Gaussian kernel. Therefore, we conclude that using the cubic kernel is the most appropriate approach. The summary is presented in Table I.

TABLE I. RESULTS OBTAINED USING THE DATA FROM THE BU-3DFE DATABASE

KERNELS	25 Images	50 Images	75 Images	100 Images	125 Images	150 Images
Linear Kernel	15	38	63	84	105	130
Cubic Kernel	21	46	71	96	121	146
Gaussian Kernel	17	39	64	86	110	135

Table I shows the ranges according to which the results are classified. It can be seen that in the range of 1-25, there are 15 linear hits, 21 successes, and 17 cubic Gaussian hits. In the range of 26-50, 38 linear hits, 46 successes, and 39 cubic Gaussian hits are identified. In the range of 51-75, there are 63 linear hits, 71 successes, and 64 cubic Gaussian hits. We conclude that the most successful range is 126-150, in which the highest percentage of successful tests is observed.

Table II provides the results of recognition represented as a percentage rate. It can be seen that using the cubic kernel allows achieving the accuracy of 97.3% corresponding to the greater accuracy obtained in the tests, 90% with the Gaussian kernel, and a minimum of 86.7% with the linear kernel.

TABLE II. RECOGNITION RATE FOR DIFFERENT METHODS USING THE $${\rm BU}{\rm -}3DFE$$ Database

KERNELS	25 Images	50 Images	75 Images	100 Images	125 Images	150 Images
Linear Kernel (%)	60.0	76.0	84.0	84.0	84.0	86.7
Cubic Kernel (%)	84.0	92.0	94.7	96.0	96.8	97.3
Gaussian Kernel (%)	68.0	78.0	85.3	86.0	88.0	90.0

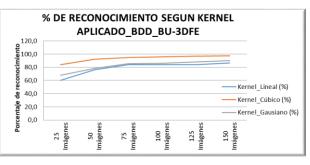


Figure 9. Percentage of classes with BDD recognition in the BU-3DFE database.

Fig. 9 is presented to visualize the trend path curves, either constant or variable depending on the rate of recognition. According to the obtained results, at the beginning, the rate of recognition corresponding to the cubic kernel tends to drop, but after the first 50 images, it levels off at approximately 97%. In turn, that of the linear kernel follows an ascending path during the interval of 101-150 images, after that it levels off at approximately 85%.

The results of the conducted experiment were compared with those related to alternative approaches of 3D facial recognition. The comparison summary is presented in Table III.

TABLE III. COMPARISON BETWEEN THE RESULTS OBTAINED USING THE PROPOSED METHOD AND THOSE PRESENTED IN THE RELATED WORKS

Methods	Databases	Rate of recognition	
Li et al. [15]	BU-3DFE	94.56%	
Cai et al. [16]	BU-3DFE	99.88%	
Derkach, Sukno [17]	BU-3DFE	81.5%	
Hariri et al. [18]	BU-3DFE	92.62%	
Hariri et al. [18]	BOSPHORUS	86.17%	
Li et al. [19]	BU-3DFE	93.9%	
Savran, Sankur [20]	BOSPHORUS	96.8%	
Savran, Sankur [20]	BU-3DFE	96.1%	
Shi et al. [21]	CASIA-3D	94.0%	
ours proposed	BU-3DFE	97.3%	

From the comparison of the results, it can be seen that the proposed method that included such steps as projecting faces using the model based on the BU-3DFE database to the three planes, then filtering and extracting characteristics to perform classification, demonstrated superior results comparing with most of the considered related works. However, it was surpassed by the approach proposed by Cai in [16] and based on the same database. According to the results obtained in the previous related studies, the researchers conclude that the data obtained from the 3D face image databases were of high importance for 3D facial recognition experiments.

IV. CONCLUSIONS

In recent years, 3D facial recognition has become more efficient and practical owing to the significant technological advancements, such as 3D high-resolution digital cameras that facilitate the process of person identification. Although there is a limited number of existing free 3D face image databases available for research purposes, it is believed that in the nearest future, many laboratories will grant open access for researchers to provide the basis for further investigation. In the present study, we achieved to obtain the remarkably good results. We observed that the proposed 3D models based on the images obtained from the BU-3DFE database achieved the rate of recognition of 97.3%. In the present treatise related to usage of 3D images, we would like to outline that 3D face image quality no longer depends on lighting. This observation was undoubtedly important in terms of its influence on the final results.

Finally, we compared the obtained results with those presented in other related works published in recent years, as presented in Table III. We found that the proposed approach is surpassed by the method developed by Cai in [16] that reaches the rate of recognition of 99.88% working with the same BU-3DFE database. However, the proposed method outperformed several other alternative approaches based on the same database achieving the rate of recognition of 97.3%. It should be noted that the proposed method has several limitations, such as the processing time of face projecting to the three planes and the extraction time of the obtained projection characteristics.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

For the present work, J.C. carried out the investigation on techniques of classification of patterns, algorithms to extract characteristics of images, projection of models of faces to the planes and finally he realized the experiments in a software of Matlab designed by the same. While N.L.S. advised the investigation and writing of this manuscript, all authors had approved the final version.

REFERENCES

- S. Keshtgar, A. Keshtgar, P. Mistry, and K. Shakib, "Assessing facial recognition after orthognathic surgery," *Br. J. Oral Maxillofac. Surg.*, vol. 57, no. 6, pp. 536-538, 2019.
- [2] R. Watts and D. Barriers, "Facial recognition as a force for good," *Biometric Technol. Today*, vol. 2019, no. 3, pp. 5-8, 2019.
- [3] H. Sadeghi and A. A. Raie, "Histogram distance metric learning for facial expression recognition," *Journal of Visual Communication* and Image Representation, vol. 62, pp. 152-165, July 2019.
- [4] V. N. Vapnik, "Statistical learning theory," Adapt. Learn. Syst. Signal Process. Commun. Control, vol. 2, pp. 1-740, 1998.
- [5] J. R. Trejo, "Support vector machines for online identification," master thesis, Center for Research and Advanced Studies of the National Polytechnic Institute, Mexico, 2006.
- [6] P. Sujitha, S. Venkatramaphanikumar, and K. Kishore, "Scale invariant face recognition with Gabor wavelets and SVM," *International Journal of Recent Technology and Engineering*, vol. 7, pp. 100-104, 2019.
- [7] C. B. Garrido and T. R. Alcaide, "Automatic applied to the recognition of vehicles. Implementation in fpsoc," thesis of the Polytechnic University of Madrid, February 2018.
- [8] M. J. Rosato, "A 3D facial expression database for facial behavior research," in Proc. the 7th International Conference on Automatic Face and Gesture Recognition, April 2006, pp. 211-216.
- [9] T. Khalil, "A survey of feature selection and feature extraction techniques in machine learning," in *Proc. Science and Information Conference*, August 2014, pp. 27-29.
- [10] M. Guillermo, "Evaluation of supervised features extraction algorithms for texture classification," final degree project, University Carlos Iii of Madrid Superior Polytechnical School D E, 2009.
- [11] L. Shen and Æ. L. Bai, "A review on Gabor wavelets for face recognition," *Pattern Analysis and Applications*, vol. 9, pp. 273-292, 2006.
- [12] A. Herreros and E. Baeyens, "Curso de programación en Matlab y Simulink," Department of Systems and Automation Engineering (DISA), University of Valladolid, 2011.
- [13] H. Moore, Matlab Para Ingenieros, Pearson Prentice Hall, 2018.
- [14] M. Garfia, "Image processing with MATLAB," M, 2014.
- [15] X. Li, Q. Ruan, G. An, Y. Jin, and R. Zhao, "Multiple strategies to enhance automatic 3D facial expression recognition," *Neurocomputing*, vol. 161, pp. 89-98, 2015.
- [16] Y. Cai, Y. Lei, M. Yang, Z. You, and S. Shan, "A fast and robust 3D face recognition approach based on deeply learned face representation," *Neurocomputing*, vol. 363, pp. 375-397, 2019.

- [17] D. Derkach and F. M. Sukno, "Automatic local shape spectrum analysis for 3D facial expression recognition," *Image Vis. Comput.*, vol. 79, pp. 86-98, 2018.
- [18] W. Hariri, H. Tabia, N. Farah, A. Benouareth, and D. Declercq, "3D facial expression recognition using kernel methods on Riemannian manifold," *Eng. Appl. Artif. Intell.*, vol. 64, pp. 25-32, 2017.
- [19] X. Li, Q. Ruan, Y. Jin, G. An, and R. Zhao, "Fully automatic 3D facial expression recognition using polytypic multi-block local binary patterns," *Signal Processing*, vol. 108, pp. 297-308, 2015.
- [20] A. Savran, "Non-rigid registration based model-free 3D facial expression recognition," *Computer Vision and Image Understanding*, vol. 162, pp. 146-165, September 2017.
- [21] B. Shi, H. Zang, R. Zheng, and S. Zhan, "An efficient 3D face recognition approach using Frenet feature of iso-geodesic curves," *J. Vis. Commun. Image Represent.*, vol. 59, pp. 455-460, 2019.

Copyright © 2020 by the authors. This is an open access article distributed under the Creative Commons Attribution License (CC <u>BY-NC-ND 4.0</u>), which permits use, distribution and reproduction in any medium, provided that the article is properly cited, the use is non-commercial and no modifications or adaptations are made.



Jose Cadena is a Computer and Computer Systems Engineer, Bachelor of Physics and Mathematics, Master of Education Sciences, mention: Educational Planning and Administration. His research areas are Exact Sciences, Artificial Intelligence and Computer Science. He is PhD student at the National University of San Marcos Lima, Peru. He is currently a Professor at the Technical University of Cotopaxi since 2001, Latacunga,

Ecuador. He is Author of articles in specialized and indexed journals, and Pre-degree and master thesis advisor.



Nora La Serna got the Doctor degree in Computer Science from the University of the Basque Country, in San Sebasti án, Spain in March 1998; Master in Computer Science, from the University of Cantabria in Cantabria Spain in July 1990; Degree in Computing, from the National University of San Marcos in Lima, Peru in 1992. She is Associate Professor of UNMSM undergraduate and graduate. Her research areas are Software engineering and

Computer Science. She is responsible for funded research projects, Author of articles in specialized and indexed journals. She is also Advisor of thesis supported by undergraduate, Master and Doctorate.