A Survey on Feature Extraction Technique for Facial Expression Recognition System

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***Abstract*—This paper presents a broad study about various feature extraction approaches in the field of facial expression recognition (FER), in this whole paper the term FER refers to facial expression recognition. The recognition of the facial expression depends on the preprocessing stage of input image and on the preciseness of the feature extraction approaches, the preciseness of the feature extraction approaches plays an important role in FER so various techniques are proposed in the literature for feature extraction which enhances the accuracy of the feature extraction approaches for the identification of the facial expression, this paper present a summary for the various feature extraction approaches proposed by various authors and a conclusion is made about current trend in feature extraction technique and the future enhancement that can be made in this area.**

Keywords—*Facial expression recognition, LBP, Gabor Filter, PCA, DCT, DWT, LPQ, SVD.*

I. Introduction

Face expression identification issued widely in human machine interplay, machine based interviews; in medical science for identification of an illness or problems like pain and depression and in health support gadgets [1]. Mechanism of facial expression identification includes preprocessing of face image, face detection, feature extraction and classification. Preprocessing stage includes removing noise and any kind of inconsistency from image; face detection step include pointingout face area in the image, pick out the face area from image and discard the rest of image. Feature extraction step include picking out pattern coefficients from the facial attribute point like eyes and lip outline which are responsible for various facial expressions. Final step is classification which includes identification of a particular facial expression based on the information gathered in the previous step [5]. Feature extraction approach is classified as appearance based features (non-geometric/non-structural features) and geometry/structural based features, geometric/structural features represents the contour and position of face part like forehead, eye, nose, lips and chin. These features are extricated to form a feature vector which is called as face geometry/structure [2]. Geometric featureextraction encodes these features using point, stretch, angle and other geometricrelationship among the component. In appearance based feature extraction method, single image filter or a filter bank is applied either on the complete image or on a part of image to extract the changes in appearance [3].Some researchers have worked on the combination of geometric based feature and appearance based feature for the efficient facial expression recognition such a work is done by Aliaa A.A Youssif and Wesam A.AAsker[4].

Basis of working domains, approach of face expression identifications divided as spatial domain and frequency domain based approach. Spatial domain approaches are LBP(Local Binary Pattern), PCA (Principal Component Analysis) and Gabor Filter. Frequency domain depended approach include DWT (Discrete Wavelet Transform), DCT (Discrete Cosine Transform) and Fourier Transform based feature extractiontechniques. In this paper, a comparative analysis of different feature extraction techniques for facial expression is carried out.

II. RELATED WORK

Local binary patterns (LBP), Principal component analysis (PCA), Gabor Filter, Discrete wavelet transform (DWT), discrete cosine transform (DCT) and Fourier Transform are explained in this section.

A. Local Binary Pattern (LBP)

This operator is given by Ojala et al.[6] is an image operator, which transform images in integer labels and their histograms are used to describe texture in images, the basic LBP operator works on the 3x3 pixel section of an image, each pixel in this section is threshold by the center pixel in a section of 3x3 pixel, a center pixel have 8 neighborhood which results in 256 different possible labels this operation can be explained in [7]. The original LBP operator had some limitations, the small 3x3 section of image cannot capture large structure which may be the outweighing feature of some texture, so it only support small spatial area. The original LBP operator is extended and it is called Generic LBP Operator which allows to take various sizes of pixel section, size of pixel section is not limited here, this is formulated as shown below [6].

$$LBP_{P,R} = \sum_{P=0}^{P-1} S\,(g_P - g_C)2^P \quad , \; S(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$$

Where g_C is the gray value of the center pixel.

g_p is the value of its neighbors.

P is the total number of involved neighbors

R is the radius of neighborhood

$g_p = \left(RCOS\left({}^{2\pi P}/_{P}\right), RSIN\left({}^{2\pi P}/_{P}\right)\right)$

$S(x)$ is the threshold function.

Many authors used template matching to implement face identification using LBP features, for template matching a Template is created for every category of facial image and the nearest neighbor categorization is applied for matching test image with the closet Template of training set, Ramchand et al. [8] has employed person dependent and person independent template matching using LBP Feature for FER [8].LBP features give good accuracy for FER with computational complexity, because the extricated LBP features depends on split parts called sub-regions, from these sub-regions LBP histograms are extricated and linked in a single vector of feature, by taking a sub-window and by moving and mounting over face image multiple sub-regions are acquired, resulting in multiple LBP histograms. Zang et al.[9] used Boosted Learning in which they used interval among comparable LBP histograms of two facial images as a discerning feature. For the features which are steady or vigorous to the rotation of the entered image, another extension of the original LBP is given this is the Uniform LBP, so in uniform LBP a regularity mensuration of pattern is needed: U("Pattern") is the count for transition from 0 to 1 or conversely when bit pattern is assumed annular, a LBP is known as Uniform if its regularity mensuration is not more than 2.For example the order 00000000(transitions:0), 00001110(transitions:2),and 11110011(transition:2) are uniform whereas the order10010011(transitions:4) and 10010101(transitions:6) is not uniform[6].

B. Gabor Filter

Gabor filters are the set of wavelet , in which each wavelet occupy energy at a particular frequency and particular orientation, expanding a signal using these set of wavelet gives the localized frequency descriptor and capture feature/energy of the signal. one of the specialization of Gabor filter is that the scale (frequency or illumination) and orientations property can be tuned (tunable), so in many applications where the object of interest may appear at different scale and orientation (pose) Gaborfilter using multi scale and multi orientation is the most suitable for feature extraction [10][11]orientation in Gabor produce the knowledge about position of edges and contours in image[12]. Gabor kernel represented as product of 2D Gaussian kernel and sinusoidal kernel by equation (1) [13, 14, 28].

$$GK(x, y, \lambda, \Theta) = \frac{1}{2\pi\sigma_x\sigma_y} e^{\frac{-1}{2}\left(\frac{x_1{}^2}{\sigma_x^2} + \frac{y_1{}^2}{\sigma_y^2}\right)} e^{i\left(\frac{2\pi x_1}{\lambda}\right)} \quad (1)$$

Where(x, y) is the position in the digital image and s_x and s_y is the standard deviation in the x and y orientation respectively,θ is the projection angle and λ is opposite of projection frequency, the variablesx_1 and y_1 are as following equation

$$\begin{cases} x_1 = x\cos\theta + y\sin\theta \\ y_1 = -x\sin\theta + y\cos\theta \end{cases} \quad (2)$$

The Gabor features are estimated by applying Convolution operation of Gabor Filter Bank $\psi(x, y)$ with entered image $I(x, y)$.

$G_{m,n}(x,y,)$=I(x,y)convolution operation$GK(\lambda, \Theta)_{m,n}$ (3)

The Gabor Filter bank $G_{u,v(x,y)}$ is complex number so a convolution operation of Gabor Filter is carried out independently for real and imaginary components as explained in following equation:

$$R_e\left(O(x, y)\right)_{m,n} = I(x, y) * R_e\left(\psi(x, y, \lambda_m, \theta_n)\right) \quad (4)$$

$$I_m\left(O(x, y)\right)_{m,n} = I(x, y) * I_m\left(\psi(x, y, \lambda_m, \theta_n)\right) \quad (5)$$

The last magnitude of Gabor Filter bank is estimated as subsequent equation:

$$|\,O(x, y)_{m,n}| = \left(\left(R_e\left(O(x, y)\right)_{m,n}\right)^2 + \left(I_m\left(O(x, y)\right)_{m,n}\right)^2\right)^{\frac{1}{2}} \quad (6)$$

C. Principle Component Analysis(PCA)

Principal component analysis is a means applied to scale-down multidimensional data sets into lower dimensions so that it is easy to do analysis of data, because there is lots of high dimension data having noisy and unnecessary dimensions, PCA has the ability to compress the data to lower dimensions keeping the most informative dimensions and rejecting the noisy and unnecessary dimensions so that the data can be fed to machine learning algorithms for classification, as its name point out it gives principal components of data, the principal components are the direction along which there is most variance in data or the directions where the data is most spread out, unlike other linear transform (DCT, DWT,DFT etc.) PCAdo not have a permanent set of basis vectors its basis vector is based on the data set, PCA has the ability to do feature extraction so it gives the most variable data component out of the sample and select the most important component from all the feature component. CA is also called as Hotelling, eigen space projection, karhunen and leove(KL) transformation [15].For a stated set of n variables$\{x_{1,}x_2 \ldots \ldots . . x_n\}$, PCA will construct a set of dominant features consecutive condition will contain true for newly composed set-the dominant feature(y_i) is the linear combination of the basic criteria(x_j) .

$$y = \sum_{j=1}^{n} a_{ij} x_j$$

Dominant feature set is a set of mutually perpendicular axes.

$$< y_i, y_j > = \sum_k a_{ik} a_{kj} = 0$$

It is an arranged set $\{y_1, y_2 \ldots \ldots . . y_n\}$in the subsidencepattern of proportionof deviation with y_1 being the maximum proportion of deviation and $y_n$being the minimum. So the small number of prime component is taken for classification [16]. Pooja et al. [17]have used 2D Gabor filter for feature extraction and mean-PCA for feature reduction on facial data.

D. Discrete Wavelet Transform (DWT)

The Discrete wavelet transform is an identification and image compression technique, wavelet transform gives wavelet coefficients which shows variation in accordance with time period at a particular scale/resolution , the terminology wavelet transform is defined as division of data or image into wavelet coefficients , as shown in the fig. 1 DWT convert facial expression image into four distinct frequency sub bands LL,LH,HL and HH, the LL sub band contain facial expression characteristic so it is extracted for the further featured evaluation

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LL Sub Band	LH Sub band
HL Sub Band	HH Sub Band

Fig.1 frequency sub band of DWT

coefficients of LL sub bands are known as approximation coefficients and coefficients of HH,HL,LH sub bands are known as detail coefficients, we compare these detail coefficients to a stated threshold value and reduce it to zero this remove the impact of noise in data , the image can be regenerated using inverse discrete wavelet transform [18][19],the wavelet transform reduces these features by 1/4 because LL sub band is 1/4 of image size,it can be applied as a feature devaluation method after the application of feature extraction approaches like Gabor which has problem of redundancy and increase in dimensionality, dwt can be applied iteratively on the extracted LL features[19].

E. Discrete Cosine Transform (DCT)

The discrete cosine transform (DCT) is used to transform and compress the train or test image in frequency domain without losing the key features in image or use the key features, DCT represent whole image as coefficients of various frequencies of cosine, in DCT low frequency components of image are extracted as it represents the higher magnitude and rest high frequency components are rejected [20].low frequency area is in low upper corner of the DCT matrix and high frequency coefficients increase crossways into lowermost right corner, extraction of low frequency area can be done by numerous techniques but the Zigzag selection technique gives the efficient selection [3][12][20].

The 1-D DCT is defined as:

$$C(u) = a(u) \sum_{x=0}^{N-1} f(x) . cos \left[\frac{(2x+1)u\pi}{2N}\right]$$

2-D DCT is defined as:

$$C(u,v) = a(u)d(v) \sum_{y=0}^{N-1} f(x,y). cos \left[\frac{(2x+1)u\pi}{2M}\right]. cos \left[\frac{(2y+1)v\pi}{2N}\right]$$

$$a(u) = \begin{cases} \sqrt{1/_M}, & for\ u = 0 \\ \sqrt{2/_M}, & for\ u = 1,2 \ldots\ldots, M-1 \end{cases}$$

$$a(v) = \begin{cases} \sqrt{1/_N}, & for\ v = 0 \\ \sqrt{2/_N}, & for\ v = 1,2 \ldots\ldots, N-1 \end{cases}$$

F. Local Phase Quantization(LPQ)

The local phase quantization(LPQ)operant is originally given by Ojansivu and Heikkila [21]as a pattern descriptor, LPQ is also robust to blur images, this structural blurring is narrated as a convolution among picture depth and a point spread function (PSF), in the frequency region it is narrated as expansion, $G = F \cdot H$ where G,F and H are the Fourier

Transform of the obscure image, Real image and the PSF respectively, if we consider simply face of the spectrum then this association result ina sum $\angle G = \angle F + \angle H$ [21][27].

G. Singular Value Decomposition(SVD)

Singular value decomposition (SVD) is consequence of linear algebra, SVD is applied in many fields but in the digital image processing SVD is used as a vigorous method for storage of vast images as a shorter and extremely feasible square ones. consider a matrix A of size $m \times n$ SVD of this matrix is defined as$A = U \sum V^T$where U is an orthogonal matrix of size$m \times m$; V is an orthogonal matrix of size$n \times n$and $\sum$ is a matrix containing singular values of A on its main diagonal having size$m \times n$, the singular values $a_1 a_2 \ldots \ldots \ldots \ldots . \ldots a_n$ are distinctive but the matrices U and V are not distinctive; in this case A must be a square matrix [22].

III. COMPARASION AND ANALYSIS

In the research papers, authors have performed their used their experiments on the still images in the built in databases like JAFFE, BU3D-FE,Cohn-Kanade etc. Various techniques given by authors in the past for the improvement of accuracy in Facial Expression Identification is mentioned in the Table 1, explaining about accuracy of technique, classification technique used and the computation time analysis required by each technique for the particular combination of feature extraction, feature reduction methods and classification method used.

Table 1: Various Feature Extraction Techniques for FER

S. No	**Method Used**	**Accuracy (%)**	**Database Used**	**Classification Method Used**	**Computation Time**
1	DCT[23]	58.3	BU3D-FE	Logistic Regression with L2 Regularization is applied for classification .One Vs Rest(OVR Setting) is used for Training 6 Regressorsindependent variables)	Because of OVR Setting it requires lesser computation, Two Fold Cross Validation is done which keeps independence among training and testing data set
2	LBP[23]	57.7	BU3D-FE	Logistic Regression with L2 Regularization is applied for classification .One Vs Rest(OVR Setting) is used for Training 6 Regressors.	Because of OVR Setting it requires lesser computation, Two Fold Cross Validation is done which keeps independence among training and testing data set
3	LBP+DCT[23]	63.0	BU3D-FE	Logistic Regression with L2 Regularization is applied for classification .One Vs Rest(OVR Setting) is used for Training 6 Regressors.	Because of OVR Setting it requires lesser computation, Two Fold Cross Validation is done which keeps independence among training and testing data set
4	LBP+LPQ[23]	63.5	BU3D-FE	Logistic Regression with L2 Regularization is applied for both classification and likelihood fusion across multiple classifiers, One Vs Rest(OVR Setting) is used for Training 6 Regressors.	Because of OVR Setting it requires lesser computation, Two Fold Cross Validation is done which keeps independence among training and testing data set
5	LBP+LPQ+ DCT[2]	65.3	BU3D-FE	Logistic Regression with L2 Regularization is applied for both classification and likelihood fusion across multiple classifiers, One Vs Rest(OVR Setting) is used for Training 6 Regressors	Because of OVR Setting it requires lesser computation, Two Fold Cross Validation is done which keeps independence among training and testing data set
6	LogGabor + Optimum Feature Selection +down sampling feature vector by a factor of 4+PCA[24]	70.0	Cohn-Kanade	MLPNN (Multi-Layer Perceptron Neural Network)	Very high due to large no of images used in training set.
7	2-Level Wavelet Decomposition+PCA[25]	77.8	JAFFE	NNC(Nearest Neighbour Classifier)	Takes large training and testing time
				Template	

8	LBP+ Template Matching[8]	79.1	Cohn-Kanade	Matching using chai square statics (x^2) is used as dissimilarity measure for histograms.	Low computational advantages.
9	Boosted LBP[8]	79.8	Cohn-Kanade	Most Discriminative LBP histogram is learnt using AdaBoost classifier and chai square statics (x^2) is used as dissimilarity measure for histograms.	Less computational complexity as compared to LBP technique.
10	DCT Zigzag Extraction [5]	80.0	JAFFE	×	×
11	Discrete Wavelet Transform Feature Extraction [5]	81.0	JAFFE	×	×
12	Gabor+LBP+LPQ+PCA+LDA[5]	82.0	JAFFE	SVM(Support Vector Machine)	×
13	Scale Gabor+PCA[13]	82.5	JAFFE	AdaBoost	×
14	Scale Gabor+Average of Each Scale Matrices+ DCT Filter[12]	83.5	JAFFE	AdaBoost	×
15	Scale Gabor+ULBP[27]	90.0	JAFFE	KNN(K-Nearest Neighbour)+Euclidean Distance(L2)	×
16	PCA+ SVD[22]	100	JAFFE	Euclidean Distance based matching classifier is used.	More computational time is required.

IV. CONCLUSION

We studied various techniques of feature extraction for facial expression recognition like DCT, DWT, LBP, Gabor Filter, LPQ, and PCA studies shows that application of a single technique for feature extraction do not perform well so combination of techniques is used in present scenario for achieving good accuracy in case of facial expression recognition, studies shows that DCT and DWT technique gives good accuracy for FER but are not robust in case of illumination changes, so Gabor Filter is used widely as a feature extraction technique, it is robust against illumination changes but it produces redundant features and has problem of high dimension so dimensionality reduction method like PCA and LBP are used in combination with Gabor Filter for feature extraction but using PCA will reduce dimensions but do not guarantees for accuracy, the averaging of all particular scale matrices are also used as a method of reducing the redundancy problem with Gabor filter, so we can conclude that a combination of feature extraction techniques with classifiers like SVM, AdaBoost, and ANN produces good accuracy for FER as shown in our table the PCA+SVD technique gives 100% accuracy but its computation time is high but the Boosted LBP technique has moderate FER accuracy of 79.8% and also it has good computational advantages.

REFERENCES

1. Choudhary, Shilpa, Kamlesh Lakhwani, and Shubhlakshmi Agrwal. "An efficient hybrid technique of feature extraction for facial expression recognition using AdaBoost Classifier." *International Journal of Engineering Research & Technology*8, no. 1 (2012).
2. Tummala, Navya Sushma, and Pnrl Chandra Sekhar. "Face recognition using PCA and geometric approach." In *Computing Methodologies and Communication (ICCMC), 2017 International Conference on*, pp. 562-565. IEEE, 2017.
3. Gupta, Sandeep Kumar, Abhishek Sharma, Anil Prajapati, Shubh Lakshmi Agrwal, and Neeraj Garg. "Gabor-Max-DCT Feature Extraction Techniques for Facial Gesture Recognition." In *Ambient Communications and Computer Systems*, pp. 767-773. Springer, Singapore, 2018.
4. Youssif, Aliaa AA, and Wesam AA Asker. "Automatic facial expression recognition system based on geometric and appearance features." *Computer and Information Science* 4, no. 2 (2011): 115.
5. Janu, Neha, Pratistha Mathur, Sandeep Kumar Gupta, and Shubh Lakshmi Agrwal. "Performance analysis of frequency domain based feature extraction techniques for facial expression recognition." In *Cloud Computing, Data Science & Engineering-Confluence, 2017 7th International Conference on*, pp. 591-594. IEEE, 2017.
6. Pietikainen, Matti, Abdenour Hadid, Guoying Zhao, and Timo Ahonen. *Computer vision using local binary patterns*. Vol. 40. Springer Science & Business Media, 2011.
7. Hablani, Ramchand, Narendra Chaudhari, and Sanjay Tanwani. "Recognition of facial expressions using local binary patterns of important facial parts." *International Journal of Image Processing (IJIP)* 7, no. 2 (2013): 163-170.
8. Shan, Caifeng, Shaogang Gong, and Peter W. McOwan. "Facial expression recognition based on local binary patterns: A comprehensive study." *Image and vision Computing* 27, no. 6 (2009): 803-816.
9. Zhang, Guangcheng, Xiangsheng Huang, Stan Z. Li, Yangsheng Wang, and Xihong Wu. "Boosting local binary pattern (LBP)-based face

recognition." In *Advances in biometric person authentication*, pp. 179-186. Springer, Berlin, Heidelberg, 200

10. Singh, S. Mangijao, Raju Rajkumar, and K. Hemachandran. "Comparative study on content based image retrieval based on Gabor texture features at different scales of frequency and orientations." *International Journal of Computer Applications*78, no. 7 (2013).
11. Rahman, Md Hafizur, Mark R. Pickering, and Michael R. Frater. "Scale and rotation invariant Gabor features for texture retrieval." In *2011 International Conference on Digital Image Computing: Techniques and Applications*, pp. 602-607. IEEE, 2011.
12. Dosodia, Priya, Amarjeet Poonia, Sandeep K. Gupta, and Shubh Lakshmi Agrwal. "New Gabor-DCT feature extraction technique for facial expression recognition." In *Communication Systems and Network Technologies (CSNT), 2015 Fifth International Conference on*, pp. 546-549. IEEE, 2015.
13. Neha, Pratistha Mathur and Sandeep Kumar Gupta. Performance Analysis of Feature Extraction Techniques for Facial Expression Recognition. International Journal of Computer Applications 166(1):1-3, May 2017.
14. Verma, Deepak, Vijaypal Dhaka, and Shubhlakshmi Agrwal. "An Improved average Gabor Wavelet filter Feature Extraction Technique for Facial Expression Recognition." *International Journal on Innovations in Engineering and Technology* 2 (2013): 1058-2319.
15. Mansour, Abdelmajid Hassan, Gafar Zen Alabdeen Salh, and Ali Shaif Alhalemi. "Facial Expressions recognition Based on Principal Component Analysis (PCA)." *arXiv preprint arXiv:1506.01939* (2014).
16. Jyotirmoy Sarkar, Snehanshu Saha, and Surbhi Agrawal, " An Efficient Use of Principal Component Analysis in Workload Characterization-A Study",2014 AASRI Conference on Sports Engineering and Computer Science (SECS 2014).
17. Yadav, Pooja, Amarjeet Poonia, Sandeep Kumar Gupta, and ShubhLakshmi Agrwal. "Performance analysis of Gabor 2D PCA feature extraction for gender identification using face." In *Telecommunication and Networks (TEL-NET), 2017 2nd International Conference on*, pp. 1-5. IEEE, 2017.
18. Soni, Karuna, Sandeep K. Gupta, Umesh Kumar, and Shubh L. Agrwal. "A new Gabor wavelet transform feature extraction technique for ear biometric recognition." In *Power India International Conference (PIICON), 2014 6th IEEE*, pp. 1-3. IEEE, 2014.
19. Agrwal, Shubh Lakshmi, Meeta Sharma, Deeksha Kumari, and Sandeep Kumar Gupta. "Improved image compression technique using IWT-DCT transformation." In *Next Generation Computing Technologies (NGCT), 2016 2nd International Conference on*, pp. 683-686. IEEE, 2016.
20. Mohseni, Sina, Hussain Montazeri Kordy, and Ramin Ahmadi. "Facial expression recognition using DCT features and neural network based decision tree." In *ELMAR, 2013 55th International Symposium*, pp. 361-364. IEEE, 2013.
21. Ahonen, Timo, Esa Rahtu, Ville Ojansivu, and Janne Heikkila. "Recognition of blurred faces using local phase quantization." In *Pattern Recognition, 2008. ICPR 2008. 19th International Conference on*, pp. 1-4. IEEE, 2008.
22. Kaur, Mandeep, and Rajeev Vashisht. "Comparative study of facial expression recognition techniques." *International Journal of Computer Applications* 13, no. 1 (2011): 43-50.
23. Tariq, Usman, and Thomas S. Huang. "Features and fusion for expression recognition—A comparative analysis." In *Computer Vision and Pattern Recognition Workshops (CVPRW), 2012 IEEE Computer Society Conference on*, pp. 146-152. IEEE, 2012.
24. S. M. Lajevardi and M. Lech, "Facial Expression Recognition Using Neural Networks and Log-Gabor Filters," *2008 Digital Image Computing: Techniques and Applications*, Canberra, ACT, 2008, pp. 77-83.
25. Dongcheng, Shi, and Jiang Jieqing. "The method of facial expression recognition based on DWT-PCA/LDA." In *Image and Signal Processing (CISP), 2010 3rd International Congress on*, vol. 4, pp. 1970-1974. IEEE, 2010.
26. Zhang, Borui, Guangyuan Liu, and Guoqiang Xie. "Facial expression recognition using LBP and LPQ based on Gabor wavelet transform." In *Computer and Communications (ICCC), 2016 2nd IEEE International Conference on*, pp. 365-369. IEEE, 2016.
27. Abdulrahman, Muzammil, Tajuddeen R. Gwadabe, Fahad J. Abdu, and Alaa Eleyan. "Gabor wavelet transform based facial expression recognition using PCA and LBP." In *Signal Processing and Communications Applications Conference (SIU), 2014 22nd*, pp. 2265-2268. IEEE, 2014.
28. Gupta, Sandeep K., and Neeta Nain. "Gabor Filter meanPCA Feature Extraction for Gender Recognition." In *Proceedings of 2nd International Conference on Computer Vision & Image Processing*, pp. 79-88. Springer, Singapore, 2018.