ANALYZING THE RESULTS FOR FACIAL EXPRESSION RECOGNITION USING VARIOUS FEATURES

HARISH KAMAT

RESEARCH SCHOLAR OF SRI SATYA SAI UNIVERSITY

Dr. A C SUBHAJINI

ABSTRACT

Face recognition technique is central in programmed facial recognitions and in observation frameworks. These explores include information from controls like neuroscience, brain research, PC vision, design recognition, picture handling and PC AI. Numerous specialists have just been completed to conquer the issues in face recognition framework as far as Recognition rate. Since this exploration considers distinctive sort of face picture information, the need to validate or to choose the personality of the individual through the contributions from the dataset officially accessible demonstrates to be a test. The consequence of the Face Recognition System [FRS] relies upon the qualities, position; include extraction and ID of the face picture to be dissected. The literary works examined and talked about uncover no vigorous technique against uncontrolled pragmatic cases which may include numerous elements all the while. In this section, the significance of the FRS improvement is talked about by covering the general thoughts and structures of recognition, significant issues and factors of human faces and looking at basic techniques and calculations.

INTRODUCTION

When the face is situated from the picture, the face arrangement and highlight extraction are the major convoluted work. This should be possible by great element extraction techniques. The component extraction techniques are sorted into four kinds: all-encompassing based strategy, highlight based technique, format based technique and part-based technique. The first three classes are every now and again talked about in written works, while the forward classification is another thought utilized in late PC vision and article recognition.

All-encompassing based strategies: Holistic-based techniques are likewise called appearance-based techniques. The whole data of the face fix is included with change by the manner in which a portrayal is produced for face recognition. Amid the previous twenty years, all-encompassing based strategies draw in the most consideration against different techniques.

Eigen face and Principal Component Analysis: The possibility of eigen face is somewhat simple. Given a face informational collection (state N faces), it first scales each face fix into a consistent size and move each fix into vector portrayal. In light of these N D-dimensional vectors it can apply the foremost part investigation (PCA) to acquire appropriate premise (each is a D-dimensional vector) for measurement decrease. The PCA technique has been demonstrated to dispose of commotion and anomaly information from the preparation set, while they may likewise disregard some key discriminative variables which might not have enormous variation but rather rule our observation. To be declared, the eigen face calculation gave critical impacts on the calculation plan for comprehensive based face recognition in the previous twenty years. In this way, it is an extraordinary beginning stage for perusers to take a stab at structure a face recognition framework.

Powerful face recognition through meager portrayal: Wright et al. proposed to utilize the inadequate sign delineation for face recognition. They utilized the over-complete database as the projection premise and connected the L1-minimization calculation to discover the portrayal vector for a human face. They guaranteed that if sparsity distinguishing proof appropriately perceived the highlights decision is never again significant. Subtleties like a measure of highlights to be satisfactorily enormous and if the scanty representation is precisely determined turns out to be progressively imperative. Imperfections inferable from occlusion and picture defilement are misused equally through these scanty mistakes concerning standard pixel in this framework.

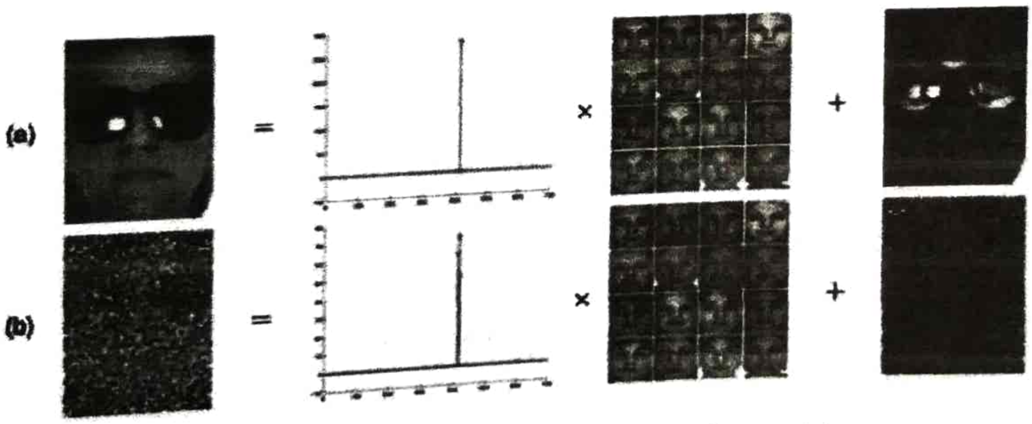


Figure 1: Sparse Representation of Occluded or Corrupted Image

EXPERIMENTAL RESULTS FOR FACIAL EXPRESSION RECOG-NITION

The exhibition of the outward appearance recognition framework is assessed for 10 subjects. For preparing a subject, an AVI document of 200 casings (50 outlines for every one of the four expressions) is recorded with a goals of 160 × 120 utilizing Logitech Quickcam Pro5000. The mouth district is situated as depicted in Section 4.2. The outward appearance is perceived for all casings in the test video. The Confusion framework is utilized for assessment. The normal execution for 10 subjects is acquired.

Haar Features

The three models, SVM, AANN and RBFNN are prepared with 36 dimensional Haar highlight vectors and their exhibitions are thought about. A preparation record with 2000 component vectors (200 for every subject) is given for preparing the SVM, 800 element vectors (80 for every subject) for the RBFNN and the AANN. The AVI documents containing the outward appearance of single and different subjects are utilized for testing. The normal execution is estimated utilizing SVM with polynomial, gaussian premise work and sigmoidal portion capacities. The strategy gives an ideal execution with gaussian premise work bit. Thus, the normal execution is estimated utilizing RBFNN with k=5, 7 and 9. An ideal execution is acquired with k=5. The AANN models with 36L 72N 9N 72N 36L, 36L 92N 14N 92N 36L and 36L 52N 4N 52N 36L structure are utilized for estimating a normal execution. The AANN model with 36L 72N 9N 72N 36L structure gives preferred execution over others. The disarray networks for outward appearance recognition for single and different faces are appeared in Tables 1 and 2.

Table 1: Confusion matrix for facial expression recognition for single face using HaarFeatures

Models	Expression	Anger (%)	Fear (%)	Normal (%)	Smile (%)
SVM with Gaussian basis function kernel	Anger	63.20	17.20	0.00	19.60
	Fear	20.00	75.84	0.00	4.16
	Normal	0.00	0.00	98.00	2.00
	Smile	2.12	4.00	2.00	91.88
RBFNN with k = 5	Anger	61.60	20.00	11.80	6.60
	Fear	19.92	68.16	0.00	11.92
	Normal	13.60	0.00	86.40	0.00
	Smile	5.68	4.32	9.68	80.32
AANN with 36L 72N 9N 72N 36L structure	Anger	56.8	23.20	10.80	9.20
	Fear	8.60	78.20	2.60	10.60
	Normal	0.00	9.00	81.00	10.00
	Smile	8.40	7.60	6.20	77.80

Table 2: Confusion matrix for facial expression recognition for multiple faces using HaarFeatures

Models	Expression	Anger (%)	Fear (%)	Normal (%)	Smile (%)
SVM with Gaussian kernel	Anger	60.20	21.80	0.00	18.00
	Fear	24.16	71.84	0.00	4.00
	Normal	6.00	0.00	94.0	0.00
	Smile	4.18	0.00	5.00	90.82
RBFNN with k = 5	Anger	53.00	21.00	16.00	10.00
	Fear	4.00	67.60	16.20	12.20
	Normal	4.40	5.60	84.80	5.20
	Smile	9.00	4.60	6.08	80.32

AANN with 36L 72N 9N 72N 36L structure	Anger	60.00	20.00	20.00	0.00
	Fear	6.00	77.98	8.00	8.02
	Normal	4.00	12.50	79.50	4.00
	Smile	10.30	9.00	3.00	77.70

Figures 2 and 3 show the performance of facial expression recognition for single and multiple faces respectively.

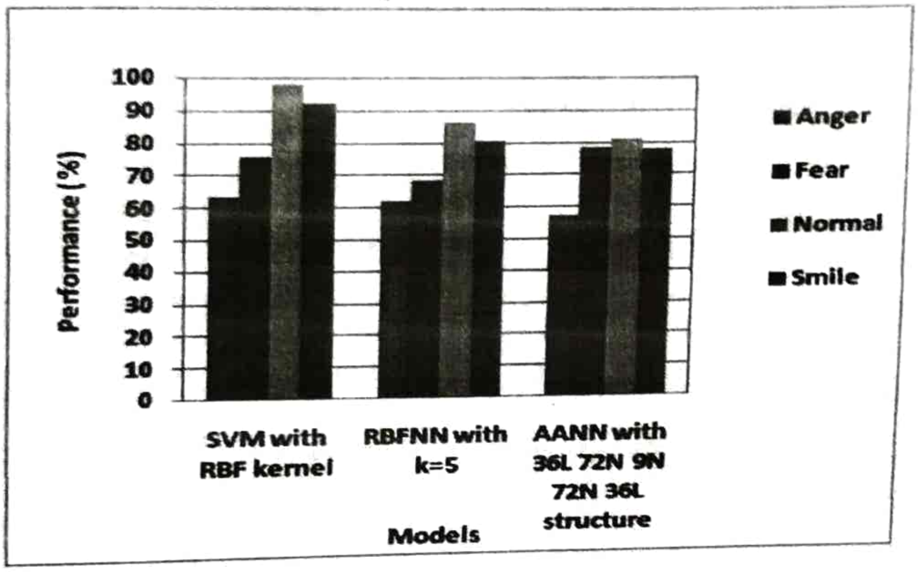
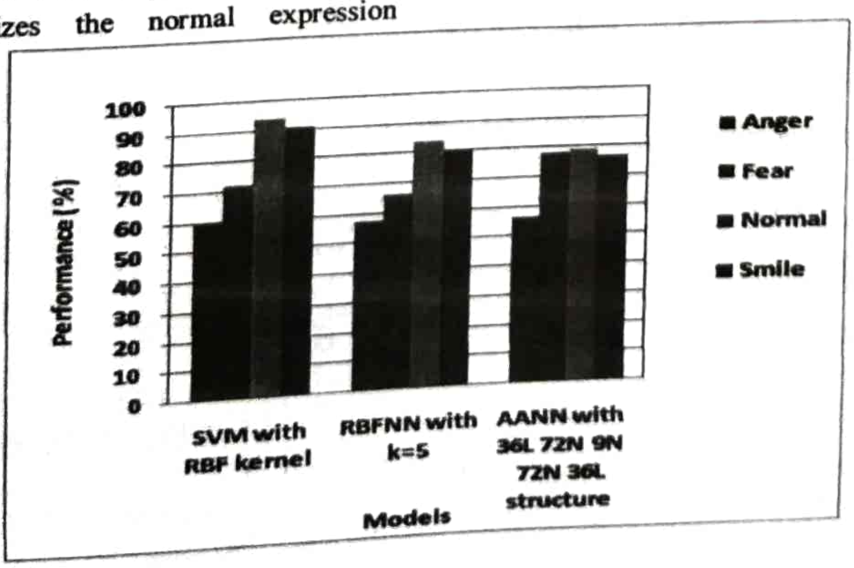


Figure 2: Performance of facial expression recognition for single face using Haar Features.

By using the Haar features, all the three models recognize the normal expression at higher percentage than the other expressions. The SVM model recognizes the normal expression correctly at the average rates of 98.00% and 94.00% for single and multiple faces, respectively.



ISSN NO: 2279-543X

Figure 3: Performance of facial expression recognition for multiple faces using HaarFeatures.

DISCRETE COSINE TRANSFORM FEATURES

In the preparation stage, the 20 most noteworthy DCT vitality coefficients are extricated from each mouth area and a sum of 2000 component vectors (200 element vectors for each subject) for SVM and 800 element vectors (80 include vectors for each subject) for RBFNN and AANN are utilized for preparing. For testing a solitary element vector with 20 most elevated DCT vitality coefficients from each mouth picture is given as contribution to the three models. The perplexity grids for outward appearance recognition for single and numerous faces are appeared in Tables 1.3.

The SVM with Gaussian premise work piece, the RBFNN with k=5 and the AANN model with 20L 40N 5N 40N 20L structure perform superior to other people. All the three models perceive the typical expression at the most noteworthy rates. Out of the three models, the AANN model accomplishes 95.52% and 95.46% normal recognition rates for single and different faces respectively.

DISCRETE WAVELET TRANSFORM FEATURES

A training file containing 56 dimensional 2000 DWT feature vectors for SVM and 56 dimensional 800 DWT feature vectors for RBFNN and AANN are used for training.

Table 3: Confusion matrix for facial expression recognition for single face using DCTFeatures

Models	Expression	Anger (%)	Fear (%)	Normal (%)	Smile (%)
SVM with Gaussian basis function kernel	Anger	47.56	26.24	13.76	12.44
	Fear	20.64	51.36	9.28	18.72
	Normal	4.60	5.20	83.40	6.80
	Smile	4.32	4.32	15.68	75.68
RBFNN with k = 5	Anger	37.20	28.56	12.56	21.68
	Fear	30.28	39.44	15.44	14.84
	Normal	7.52	0.00	83.52	8.96
	Smile	8.92	6.92	7.08	77.08
AANN with 20L 40N 5N 40N 20L structure	Anger	60.36	20.36	8.72	10.56
	Fear	10.24	74.24	5.76	9.76
	Normal	0.00	0.00	95.52	4.48
	Smile	5.68	3.68	6.32	84.32

The SVM with Gaussian basis function, RBFNN with k=5 and the AANN model with 56L 112N 14N 112N 56L perform better than the others.

ISSN NO: 2279-543X

CONCLUSION

It is concluded that various unique commitments are made to empower face and outward appearance recognition. Innovative work of novel structures for synchronous face and expression recognition, face recognition, and outward appearance recognition would be important to analysts, since expression variation is a difficult issue in current best in class face recognition frameworks. Then again, current methodologies are not fit for perceiving facial variations viably inside these present reality applications.

REFERENCES

[1]. Tiwari, Ashish and Mohan Manubai Trivedi, "Face Expression Recognition by Cross Modal Data Association.", IEEE Transactions on Multimedia, Vol.15, No.7, pp.1543-1552, 2013.

[2]. Song and Mingli, "Image ratio features for facial expression recognition application." IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, Vol.40, No.3, pp.779-788, 2010.

[3]. Lev, Yanpeng and Shangfei Wang, "A spontaneous facial expression recognition method using head motion and AAM features." IEEE Second World Congress on Nature and Biologically Inspired Computing (NaBIC), pp.334-339, 2010. [MBS2014] Majumder, Behera

[4]. Tariq and Usman, "Recognizing emotions from an ensemble of features." IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, Vol.42, No.4, pp: 1017-1026, 2012.

[5]. Valstar and Michel Francois, "Meta-analysis of the first facial expression recognition challenge." IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, Vol. 42, No.4, pp.966-979, 2012.

[6]. RahulMathavan, and YogaChandran, "Facial Expression Recognition in the Encrypted Domain based on Local Fisher Discriminant Analysis." (2013): 1- 5,2013.