Facial Expression Recognition: A Survey on Local Binary and Local Directional Patterns

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Abstract. Automated facial and emotional recognition has been extensively applied in computer science, medical neuroscience, law enforcement and crowd monitoring. The study evaluates use of popular feature descriptors, Local Binary Pattern(LBP) and Local Directional Pattern(LDP) variants in facial expression recognition feature extraction. It then classifies results of the local facial features of major emotional states, namely neutral, anger, fear, extraction and expression identification using a combined ratio of classifiers called Voting Classifer. Databases used in the experiments involved Cohn-Kanade Database and the Google-set datasets and the expression classification rate of around 99.13% was achieved. The proposed solution included a hybrid of Local Directional Pattern(LBP), Local Directional Pattern(LDP) as the feature extraction algorithms and weighted ensemble of classifiers called voting classifier classification algorithm.

1 Introduction

Facial expression identification automation has benefited fields like medicine, security, accounting, education and computing [3]. Widespread use of automated facial expression analysis has been witnessed in identity management systems, crowd surveillance, crime control and security control systems [3]. The human face's emotions guides a person's gender, attractiveness, age, personality and other characteristics as well. Automated facial recognizers have been applied in intelligent networks and transportation systems for drowsiness detection as well in the internet of things. For the deaf, sign languages use facial expressions to do grammar encoding in communication. Indications for sickness, stress, deception and happiness are derived through micro expressions since they leak behavior control. Facial expressions are either voluntary or intentional and in some cases non-voluntary or natural responses to stimuli[18, 1]. Based on Darwin's emotions theory, fear arises when one opens the eyes or raises eyebrows[18]. Anger manifests when one has open eyes and raised nostrils[9]. One will be showing contempt by looking the other way. Surprise is shown by opening both the mouth and eyes wide[9]. AlchemyAPI, Emotiva, IBM Watson as well Windows Azure are some of the major facial emotional recognition industrial APIs used in sentiment analysis and crowd expression detection.

2 Literature Review-Facial Expressions

Key expressions include sadness, joy, neutral, surprise, fear and anger. Facial expression recognition algorithms research in personalised gaming has been successfully researched[9, 19]. Chronic pain identification has been successfully identified using facial expression analysers in hospitals and places of work[18, 1]. Automated smile identification was also used in hospitals with focus on chronic patients and young babies using real time embedded solutions[3]. Facial expressions for different emotions have been extracted using various feature extraction algorithms together with various supervised and unsupervised learning classifiers. Local binary patterns and local directional patterns, both local algorithms have been used successfully to identify all the different expressions [13][15] with holistic algorithms like Principal component analysis achieving great accuracy[20]. Facial expression feature extraction is done using namely geometric and appearance based feature extraction. The former method computes the locations and shape data using various facial parts example like nose, mouth, eye, distance between nose and the eye region. These facial parts are then combined into a feature vector which represents the geometry of the face[11]. The feature vector classification accuracy is affected by the dimensional properties and redundancy of some of the features. Appearance based algorithms represent a face as multiple raw intensity images where a given image is made up of multi-dimensional vectors. Statistical algorithms are used to extract feature space from the images. Some of the features in the given feature vectors are redundant taking for instance non-discriminating features which bring complexity and reduced recognition accuracy rates[1, 2]. The research expands facial expression recognition work using LBP and LDP and voting classifier [18].

2.1 Holistic and Local Algorithms

Holistic and local features play a great role in facial expression analysis[12][7]. Holistic algorithms will extract the entier facial image whereas the local algorithms consider local facial subregions like nose, mouse and ears. The latter is position and face orientation dependent as well. Popular holistic algorithms include PCA(principal component analysis), discrete cosine transform(DCT)[7] and Fisher faces as well. Holistic algorithms are good because they is no information loss even after concatenation since they focus on specific points of interest which are not impacted by dimensional reduction[11]. Local features are extracted by algorithms such as Local Gabor Feature Vectors (LGFV)[11], Local Binary Patterns (LBP) and Local Directional Patterns.

2.2 Local Binary Patterns (LBP)

Local Binary Patterns divide an image into local subregions for feature extraction and or texture analysis in the field of facial recognition. This assists in overcoming facial recognition challenges like occlusion or non-rigidness in facial images[11, 18]. The localisation of feature extraction allows classification in both coloured or gray level images with no variance [13, 19]. The localised feature vectors are derived from feature extraction where each facial subregion is concatenated into a single histogram of feature vectors which is classified by traditional machine learning classifiers like k-nearest neighbour, random forest and voting classifiers [13, 18]. Local Binary Pattern (LBP) [12, 13] variants have been used in facial and emotion recognition and have exhibited invariancy and robustness to illumination changes and computational simplicity [13]. Various LBP variants were proposed as LBP extensions and modifications were done to improve facial recognition accuracy[12, 15].

2.3 LBP variants

Various LBP variants have been proposed and used in facial expression recognition. LBP variants included symmetric (CS-LBP) which is a modified LBP algorithm, Rotated Local Binary Patterns(RLBP), Uniform local binary patterns(ULBP) as well as LBPNet which is applied LBP on Convolutional Neural Networks (CNN)[12] ,[18]. LBPs have been combined with Gabor features in facial expression application succesfully[12][15]. Rotated Local Binary patterns which consider LBP signs of diferences when calculating final desciptors have also been applied in emotional recognition feature extractions[15]. Symmetric (CS-LBP), an enhanced LBP algorithm with longer feature vectors, higher dimensions and more robustness than the normal LBP has also been applied in facial expression feature extraction experiments with more success on flater images[12, 18, 15]. Enhancements have been applied to the LBP using the SIFT descriptors[1][2].

2.4 LBP variants with Convolutional Neural Networks

Deep learning allows for high level data representation by going through several conv(processing) layers and allows for dual feature extraction and classification. Convolutional neural networks (CNN)have been implemented with success in facial expression recognition[16].Yu and Zhang used the EmotiW idataset with 5 convolutional layers to recognised facial expressions[16]. Since CNN does both it has achieved better results than traditional feature extration algorithms like LBP and LDP. Binary Patterns with Encoded Convolutional Neural Networks were successfully applied for texture recognition and remote sensing[16]. LBPNet also applied LBP and Convolutional Neural Network (CNN) deep learning topology and replaced deep learning training kernels with Local Binary Pattern computer vision descriptors[17]. This was found to be less expensive approach and achieved with little data[17].

2.5 Local Directional Patterns

Local directional pattern algorithms use compass masks to encode directional facial local image components. The image is split into subregions and the feature extractions are grouped into one histogram to classify. More prominent regions get picked up in generating the more pronounced regions[12][15]. Different experiments were done where the descriptors accuracy where measured given the noise, different lighting conditions and varying time conditions and the LDP descriptors exhibited robust resistance to noise [12, 15]. The top k-directional bits are given the value of 1 and the remaining bits take the value of zero. The image was then split into small regions where histograms were combined into an LDPv descriptor. Encoding is done using edge detection algorithms on more prominent edges based on the Kirsch algorithm which applies image convolution [12] ,[18]. Edge responses are invariant to noise and non-monotonic illumination changes [15, 18].

3 Methods and Techniques

3.1 Facial Expression Databases

Facial images were retrieved from the Googleset database and CK+ dataset. The dataset images depicted different facial expressions reflecting various emotions. The given emotions ranged from fear, sadness, happiness/joy, disgust to neutral[17]. The study participants performed several action units and facial displays and the images changed from neutral to peak through seven categories[22]. The google facial dataset was chosen due to its small dataset structure and the CK+ due to its large dataset and different races. The CK+ dataset has around hundred individuals of American, Asian and Latin origin[22]. The Cohn-Kanade (CK) AU-coded expression dataset included over 100 students aged in their teenage years and early adulthood[18]. The facial Google dataset was also used. Around an eighth of the dataset subjects were African American.

3.2 Preprocessing Face Alignment, Normalization and Dimensional reduction

Noise was eliminated by re-sizing the data so that all images had same dimensions. The images were initially converted into grey level images. Kirsch masking at 45 degrees rotation was used to extract edge responses in eight different directions. During normalization, the images went through standardization using size, pose and illumination as key parameters in relation to the image. Dimensional reduction was implemented using Principal component analysis (PCA) algorithm.

3.3 Feature Extraction

Feature extraction for local features of the images into the histogram was done based on Local Binary Patterns and Local Directional Patterns. For the 2 databases, Voting classifiers were then applied on the trained data. Accuracy and performance of the algorithms was measured on the data. A given LBP M,N operator is represented mathematically as follows

$$LBP_(M,N)(m_x,n_x) = \sum_{V-1}^{V=0} q(p_x - p_c)2^V. \quad (1)$$

For the LBP equation, the neighbourhood being depicted as M-bit binary resulting in V distinct values for a specific LBP code. The gray level is in the form of 2 V-bin unique LBP codes. For the Local Directional Number Pattern[18]. The facial expression images were subdivided into subregions where LDPx histograms were retrieved and combined into a single descriptor[18].

$$LDP_x(\sigma) = \sum_{K}^{r=0} \sum_{L}^{r=0} f(LDP_q(o,u),\sigma). \quad (2)$$

3.4 Classification

For both Local Binary Patterns(LBP) and Local Directional Patterns(LDP), the feature vectors were used for classification by machine learning classifiers and the trained dataset was also used as input into the deep learning neural network. Various machine learning classifiers, namely random forest, neural networks, k-nearest neighbor, 4.5 decision tree classifiers and support vector machines were examined. They were also combined in the form of a combined classifier called Voting Classifier. EnsembleVoteClassifier is a meta-classifier that combines various machine learning classifiers for classification via majority, weighted or probability voting[12]. The Ensemble classifier eclf is a combination of clf1, kNearest Neighbour with weight 0.35, clf2 representing Support Vector Machine with weight 0.2 and classifier clf3 with weight 0.45.The modal eclf classifier accuracy is then taken as the accuracy. We applied cross validation to ensure there is reduced overfitting.

$$eclf = EC(clfs = [clf1, clf2, clf3], weights = [0.35, 0.2, 0.45]) \quad (3)$$

EC in the above equation represents the EnsembleClassifier with 3 classifiers. The facial images were then saved in a MySQL Database in the form of feature vector forms for facial expressions. The expression classes identified included neutral, happiness, anger, fear, disgust and sadness(sorrow).

3.5 LBP Convolutional Neural Network Expression Recognition

Both the CK+ and Googleset databases were processed using 5 CNN convolutionary layers after the feature vectors had been already been extracted. The google python 2.7 tensorflow library was used in this process and accuracy results for each emotion measured.

4 Facial Recognition and Expression Results

The experiment included firstly finding the modal ensemble classifier which was then used in Local Binary Pattern feature vector classification and this is explained in section 4.1. Several experiments were then run to compare facial expression accuracy firstly using Local Binary pattern variants with the modal ensemble classifier(section 4.2).

The same data was also run against a CNN variant Local Binary Pattern. The facial recognition and expression classification results were then compared respectively in sections 4.2 to 4.5. The 2 resulting algorithms were then compared in terms of accuracy, cost, time and simplicity in the conclusion section 4.6.

4.1 Finding Modal Ensemble Voting Classifier

The classification used cross-validation based on a training/test ratio of 6 to 4 ratio on the image classification algorithms. The classification results are detailed in diagram in Figure 1. The voting classifier combination for kNN, support vector machines(SVM), random forest(RF) and C4.5 decision tree(DT) with various ratios of the different classifiers[18]. Around 100 variations of the classifiers were executed with different classifier ratios(classes) to find the modal combination. The table in Fig. 1. shows 4 samples of randomly picked 100 ratio combinations executed with a 5:2:1:2 ratio, 3:1:3:4 ratio, 6:1:2:1 ratio and 4:1:4:1 ratio which was class 9, 34, 45 and 25 respectively. The modal accuracy also shown,class 25 was the one where kNN had high ratio which is 7:1:1:1 and this gave an accuracy for 99.13% for the CK+ database and 99.23% for the Google data-set. The combinations where decision trees were dominant showed worst performance in the tests as shown by class 45. The choice of the ensemble classifier was based on the LDP and ELBP(8,2) feature extraction combination.

Fig. 1. Voting Meta Classifier

classifier	**class 9**	**class 34**	**class 45**	**class 25**	**class 100**
kNearest Neighbour	x_1 * 0.5	x_1 * 0.3	x_1 * 0.2	x_1 * 0.7	x_1 * 0.4
Support Vector Machines	x_2 * 0.2	x_2 * 0.1	x_2 * 0.1	x_2 * 0.1	x_2 * 0.1
Random Forest	x_3 * 0.2	x_3 * 0.3	x_3 * 0.1	x_3 * 0.1	x_3 * 0.4
c4.5 Decision Tree	x_4 * 0.1	x_4 * 0.3	x_4 * 0.6	x_4 * 0.1	x_4 * 0.1
Accuracy(CK+ Data)	0.79	0.67	0.23	0.9923	0.86
Accuracy(Googleset)	0.72	0.64	0.26	0.9913	0.81

GoogleSet Data	kNN+	Support Vector Machine	RF	Voting Classifier	Ave Time(s)	CK+ Data	kNN+	Support Vector Machine	RF	Voting Classifier
$LBP_{8,2}$	93.09%	97.12%	97.16%	97%	52.31s	$LBP_{8,2}$	92%	97%	97.6%	97%
$LBP_{16,2}$	94.26%	98.03%	97.28%	95.99%	44.23s	$LBP_{16,2}$	93%	98%	97%	96%
CS-$LBP_{8,2}$	93.51%	97.98%	97.33%	97.86%	51.87s	CS-$LBP_{8,2}$	93%	96%	96%	98.56%
CS-$LBP_{16,2}$	94.05%	96.92%	96.08%	98.31%	53.45s	CS-$LBP_{16,2}$	92.5%	97.2%	96.08%	97.1
$ELBP_{16,2}$	91.3%	91.02%	96.29%	97.09%	55s	$ELBP_{8,2}$	89%	87.2%	96%	96.9%
$ELBP_{16,2}$	88.21%	87.12%	95.75%	96.91%	52s	$ELBP_{16,2}$	85%	85%	96.5%	96.1%
$LTP_{8,2}$	89.71%	96.31 %	96.77%	96.74%	51s	$LTP_{8,2}$	85.7%	95.1 %	97%	95.54%
$LTP_{16,2}$	88.3%	96.44 %	97.42%	97.24%	54s	$LTP_{16,2}$	86.27%	95 %	97%	96.33%
$RLBP_{8,2}$	86.1%	97.01 %	96.8%	97.48%	53s	$RLBP_{8,2}$	85.1%	95.4 %	96.8%	96.61%
$RLBP_{16,2}$	84.3%	97.21 %	97.09%	97.64%	51s	$RLBP_{16,2}$	85.3%	95.21 %	96%	97.66%
LDP+$ELBP_{8,2}$	94.18%	97.81%	96.92%	99.13%	55.23s	LDP+$ELBP_{8,2}$	93.1%	98.2%	97.88%	99.23%
LDP+$ELBP_{16,2}$	94.78%	97.99%	97.02%	99.03%	55.6s	LDP+ $ELBP_{16,2}$	94.3%	97.45%	98.39%	99.27%
LBP+CNN(99.63%)					1620s	LBP+CNN(99.77%)				

Fig. 2. Classifier for CK+ and GoogleSet Dataset

4.2 Facial Recognition Classification Results

The algorithms used in the study included LBP variants namely symmetric CS-LBP, local ternary LTP, the rotated RLBP , enhanced LBP , LBP with CNN and a combined algorithm with LDP and ELBP algorithm. Various classifiers were used namely k-Nearest neighbor, Support Vector Machine, Random Forest(RF) and a Voting Classifier. The modal accuracy, class 25 was the one where kNN had high ratio which is 7:1:1:1 and this gave an accuracy for 99.13% for the CK+ database and 99.23% for the Google data-set. The combinations where decision trees were dominant showed worst performance in the tests as shown by class 45. The choice of the ensemble classifier was based on the LDP and ELBP(8,2) feature extraction combination.

4.3 Facial Expression Results: Small Datasets-Googleset

The facial expression results were based on the following emotions namely anger, disgust, fear, happy or joyness, sadness,neutral, surprise plus contempt. The results are summarised in the following namely figure 3 and 4 based on the Googleset data. The google set data was a small dataset and experiments were carried out from 100 images up to 1500 images though the best results picked were for 75 images as well as for 181 images all achieving an average well beyond 99 percent. Due to the small dataset the 75 images were only able to pick 4 emotions hence the reason the 3 emotions were all showing zero accuracy. For the Googleset large dataset test with the best accuracy a 1500 images were trained and using a two thirds classification ratio, 1000 images were classified into the 7 emotions.

Fig. 3. Google Set Dataset Facial Expression Recognition Small Dataset-75 images

	precision	recall	f1-score	support
anger	1	1	1	16
disgust	0.98	1	0.99	44
fear	1	0.92	0.96	12
happy	1	1	1	3
disgust	0	0	0	0
fear	0	0	0	0
happy	0	0	0	0
avg/total	0.99	0.99	0.99	75

Confusion Matrix								
anger	[[**16,**	0,	0,	0,	0,	0,	0]	
disgust	[	0,	**44,**	0,	0,	0,	0,	0]
fear	[	0,	1,	**11,**	0,	0,	0,	0]
happy	[	0,	0,	0,	**3,**	0,	0,	0]
disgust	[	0,	0	0,	0,	0,	0,	0]
fear	[	0,	0	0	0,	0,	0,	0]
happy	[	0,	0,	0,	0	0,	0,	0]]

Fig. 4. Google Set Dataset Facial Expression Recognition-181 images

	precision	recall	f1-score	support
anger	1	1	1	16
disgust	1	1	1	44
fear	0.92	1	0.96	12
happy	1	1	1	39
neutral	1	0.94	0.97	18
sadness	1	1	1	23
surprise	0.97	0.97	0.97	29
avg / total	0.99	0.99	0.99	**181**

Confusion Matrix								
anger	[**16,**	0,	0,	0,	0,	0,	0],	
disgust	[	0,	**44,**	0,	0,	0,	0,	0],
fear	[	0,	0,	**12,**	0,	0,	0,	0],
happy	[	0,	0,	0,	**39,**	0,	0,	0],
neutral	[	0,	0,	0,	0,	**17,**	0,	1],
sadness	[	0,	0,	0,	0,	0,	**23,**	0],
surprise	[	0,	0,	1,	0,	0,	0,	**28**]

4.4 Facial Expression Results for Large Datasets-CK+

CK+ database experiments involved tests with a small dataset of 500 up to a range of 4000 images as well. The accuracy in both scenarios was impressive averaging 99%+ in the larger dataset and 98% in the smaller dataset. Only 6 emotions were measured. As indicated in the overral classification table the Voting Classifier showed supreme accuracy compared to the individual classifiers. Sadness was the best accuracy emotion whilst neutral showed few individuals who were incorrectly classified.

Fig. 5. CK+ Dataset Facial Expression Recognition Large dataset(1400 images)

	precision	recall	f1-score	support
anger	0.98	1	0.99	317
disgust	0.98	0.99	0.99	214
fear	1	0.99	0.99	230
happy	0.99	0.99	0.99	276
neutral	1	0.99	1	214
sadness	1	0.98	0.99	149
avg/total	0.99	0.99	0.99	**1400**

	Confusion Matrix						
anger	[[**317,**	0,	0,	0,	0,	0],	
disgust	[	2,	**212,**	0,	0,	0,	0],
fear	[	2,	0,	**228,**	0,	0,	0],
happy	[	1,	3,	0,	**272,**	0,	0],
neutral	[	0,	1,	0,	1,	**212,**	0],
sadness	[	0,	0,	1,	2,	0,	**146**]]

Fig. 6. CK+ Dataset Facial Expression Recognition small dataset(250 images)

	precision	recall	f1-score	support
anger	0.99	1	0.99	70
disgust	1	1	1	44
fear	1	1	1	32
happy	1	1	1	40
neutral	1	1	1	36
sadness	1	0.96	0.98	28
avg/total	1	1	1	250

	Confusion Matrix						
anger	[**70,**	0,	0,	0,	0,	0]	
disgust	[	0,	**44,**	0,	0,	0,	0]
fear	[	0,	0,	**32,**	0,	0,	0]
happy	[	0,	0,	0,	**40,**	0,	0]
neutral	[	0,	0,	0,	0,	**36,**	0]
sadness	[	1,	0,	0,	0,	0,	**27**]

4.5 Results Analysis

LDP+ELBP feature extraction classified by a voting classifier gave accuracy of 99.23 percent and 99.13 on the Google-Set and CK+ databases which was the modal accuracy. This was much improved accuracy compared to other comparative LBP variant algorithms. The tests results from the experiments included runs of around a century of images, medium sized runs of a thousand to 2000 images and huge datasets beyond 5000 images for the CK+ database. The results did support the theory that large or small datasets have no impact on accuracy on LBP algorithms[18] with voting classifiers and will give high accuracy irregardless. The LDP algorithm, an edge detection algorithm's smoothening of the edges capability based on the Kirsch algorithm aided in removing edge noises from the grey level images. The google-set data also had impressive accuracy when classified by an ensemble classifer with accuracy of 99.23% being the modal classification result. The classifier with better results was the Voting Classifier and it showed consistent results for low number of images from around 100 and also for medium range of images which is around 1000 as well as for huge number of images ranging around 10 000 facial images as well.

4.6 Conclusion

The study's experiments results show the Local Binary Pattern and Local Directional Pattern classified by a Voting Classification Algorithm where kNearest Neighbour has the dominant weight(seventy percent) improves facial emotions accuracy. Although higher facial expression classification rates were achieved by the proposed methods, there is still some issues which should be furthered addressed such as finding the optimal threshold for each database automatically, or applying the proposed algorithm with other features, in the purpose of improving the recognition rate. Therefore, the hybrid LDP+ELBP Feature Extractor with a Voting Classifier operators presented in this study gave improved accuracy for facial emotion recognition compared to a uniform LBP or LDP on their own. Happiness in all the cases recieved the highest classification accuracy for both google dataset and the CK+ dataset as well ranging from around 90-100 percent.

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