Boosting Facial Expression Recognition in a Noisy Environment Using LDSP-Local Distinctive Star Pattern

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Abstract

This paper presents a local feature descriptor, the Local Distinctive Star Pattern (LDSP), for facial expression recognition. The feature is obtained from a local 3x3 pixels area by computing the directional edge response value. Each pixel is represented by two 4-bit binary patterns, which is named as LDSP feature for that pixel. Each face is divided into 81 equal sized blocks and histogram of LDSP codes from those blocks are concatenated to build the feature vector for classification. The recognition performance of our descriptor is tested on popular JAFFE dataset with Support vector Machine (SVM) as classifier. Extensive experimental results with prototype expressions show that proposed LDSP descriptor is superior to existing appearance-based feature descriptor in terms of classification accuracy on static image.

Keywords: *Facial Expression Recognition, Image Processing, Local Feature, Pattern Recognition, JAFFE, Computer Vision*

1. Introduction

Over the last few years, interaction between human and computers has become an interesting and challenging problem due to the advancement in computer software and hardware. For an effective human computer interaction, computers should be able to communicate naturally with the user, in the same way that humans communicate with other humans. In human-to-human interaction, facial expression is a vital issue, which contributes 55% of the total communication [1]. P. Ekman *et al.* [2] carried out a detailed research on human communication and found that facial expressions are universal and innate. P. Ekman observed that members of an isolated tribe in Papua New Guinea could reliably identify some expressions of emotions in photographs such as joy, surprise, anger, fear, sadness and disgust. There are two methods to represent facial features responsible for expressions: geometric based methods and appearance based methods [3]. Geometric methods extract information from the location and shape of facial components e.g. eye, nose or mouth. Appearance based methods notices the appearance change of the face e.g. wrinkles, bulges and furrows. The main problems with the geometric based methods are that they are sensitive to noise and tracking errors. On the other hand appearance based methods are less dependent on initialization and can encode patterns from both selected small or large area that are significant for facial expression recognition (FER). However, appearance features do not generalize as well across individuals as they encode specific appearance information. This paper investigates a novel appearance based feature extraction technique using popular dataset and machine vision learning approaches to generalize across individuals and pose.

A new facial representation strategy using Local Binary Pattern (LBP) was proposed by T. Ahonen *et al.* [4]. The LBP value at the referenced center pixel of a 3x3 pixels area is calculated using the gray scale color intensities of the referenced pixel and its neighboring pixels. G. Zhao *et al.* [5] applied facial dynamic texture data with Local Binary Pattern on the Three Orthogonal Planes (LBP-TOP) and Volume Local Binary patterns (VLBP) to have motion and appearance. In her earlier work [6], she tested with the two-dimensional (2-D) discrete cosine transform (DCT) over the entire face image but got less accuracy on the facial expression recognition. An extension to the original LBP operator called LBPRIU2 was proposed by [7]. It reduces the length of the feature vector and implements a simple rotation-invariant descriptor. Although LBP features achieved high accuracy

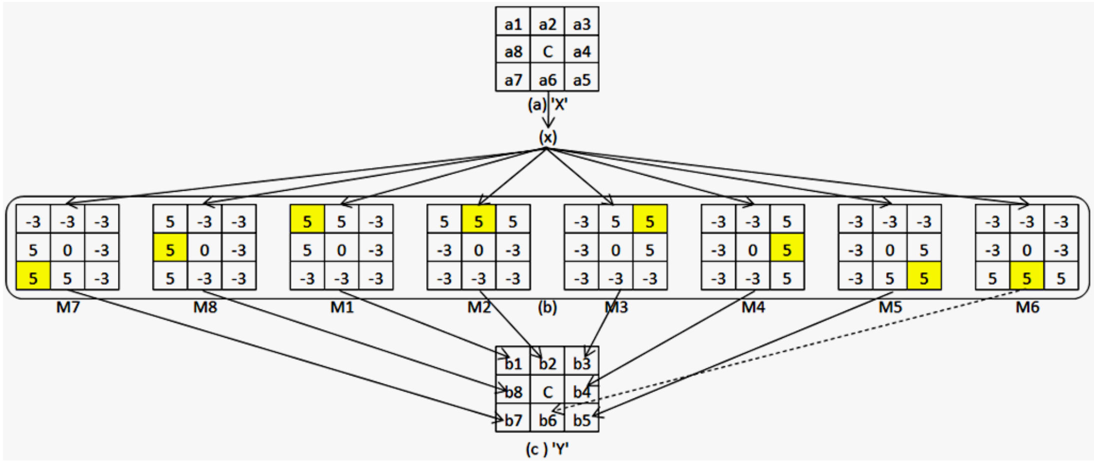

Fig. 1: (a) Local 3x3 pixels region where a(1-8) are the gray color intensity of corresponding pixels, (b) Kirsch edge response masks in eight directions, M(1-8), (c) Obtained edge response matrix.

rates for facial expression recognition, LBP extraction can be time consuming. To build facial expression recognition system, Yang *et al.* [8] used local binary pattern and local phase quantization together. Kabir *et al.* [9] proposed LDPv (Local Directional Pattern- Variance) by applying weight to the feature vector using local variance and found it to be effective for facial expression recognition. He used support vector machine as a classifier. Huang *et al.* [10] used LBP-TOP (LBP on three orthogonal planes) on eyes, nose and mouth. They developed a new method that can learn weights for multiple feature sets in facial components.

Proposed feature representation method can capture more texture information from local 3x3 pixels area. The referenced pixel is surrounded by eight pixels. Each of these eight pixel's gray color intensity is used twice to build the binary pattern whereas in LBP it is only once. It is robust to monotonic gray-scale changes caused, for example, by illumination variations. It is more consistent in the noisy environment edge response magnitude is more stable than pixel intensity. It is appropriate for large-scale facial dataset. In comparison with LBP [11] or LBP_{RIU} [7], proposed method performs better both in time and classification accuracy.

The rest of the paper is organized to explain the proposed local feature representation method and system framework in section 2, selecting features in section 3, data collection and experimental setup in section 4, results and analysis in section 5 and conclusion in section 6.

2. Methodology and System Framework

LDSP (Local Distinct Star Pattern) computes local feature of two four-bit binary patterns for each pixel surrounded by eight neighboring pixels in two steps.

Step 1:

Each pixel, which is surrounded by eight pixels, can be denoted as a 3x3 pixels region. In step 1, Kirsch edge response masks in eight directions is applied on local 3x3 pixels region as shown in Fig. 1. b1 is calculated as

$$b1 = M1.*('X') = 5*a8+5*a1+5*a2-3*a3-3*a4-3*a5-3*a6-3*a7$$
$$b2 = M2.*('X') = 5*a1+5*a2+5*a3-3*a4-3*a5-3*a6-3*a7-3*a8$$

and similar way b3 and b8.

Step 2:

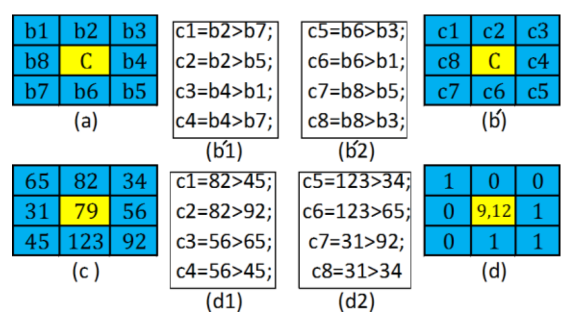

Fig. 2: Example of obtaining 2, 4-bit binary patterns from local 3x3 pixels area. (a) 3x3 pixels region. (b′) Replaced pixels values using (b′1) and (b′2), (c) Local 3x3 pixels region with gray color intensity values. (d) Obtained binary pattern, pattern1 (d1) ='c1c2c3c4'=1001 =9 and pattern2 (d2) ='c5c6c7c8'=1100 =12

The edge response matrix obtained from step 1 is used here to build two 4-bit binary patterns. In

Fig. 2 (a), starting from the top left corner to the clockwise directions, the pixels are denoted as b1 to b8. Two 4-bit binary patterns are formulated from this region.

Pattern-1= ‘c1c2c3c4’ where c1, c2, c3 and c4 are binary value of either 0 or 1. Value of c1 is 1 if b2>b7 is true and 0 if it is false. Similarly, the value for c2, c3, c4, c5, c6, c7 and c8 is obtained using comparisons shown in

Fig. 2 (b1) and (b2) to build the Pattern-2. Now the center of referenced pixel ‘C’ is represented by these two 4-bit binary patterns. A detailed example of obtaining binary patterns from a local 3x3 pixels region of a gray scale image is shown in Fig-2 (c) and (d).

A 4-bit binary pattern can have at most 16 different bit combinations. Each combination is considered as a separate bin. So for two 4-bit binary patterns, 32 bins are needed, 16 for the first pattern and 16 for the second pattern. This pattern named as LDSP (Local Distinct Star Pattern) of that pixel. After applying LDSP on each pixel of the input image, histogram for each block is calculated. Feature vector is calculated concatenating all histograms from 81 blocks. Calculating histogram from block contains more location information than calculating histogram from the whole image [12].

The facial expression recognition system (FERS) framework is shown in Fig. 3

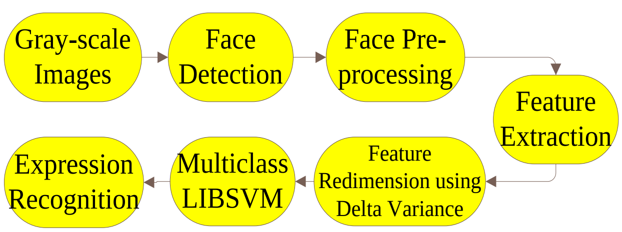

Fig. 3: Proposed System Framework

- Load the image and convert it to gray scale if in different format.
- Detect the face, resize it to 99x99 pixels and divide it into 9x9 blocks of 11x11 pixels each.
- Compute LDSP value for each pixel.
- Construct the histogram for each block.
- Concatenate the histograms of all 81 blocks to get the feature vector.
- Project the long feature vector onto lower dimension using Delta Variance.
- Use LIBSVM, a multiclass classifier to run a ten-fold non-overlapping cross validation.

3. Feature Dimensionality Reduction Using Delta Variance

For the proposed method, feature vector dimension is 32x81=2592. Not all the features in this feature vector are equally informative. Since the main duty of these features is to differentiate expressions, therefore feature having high variance between the classes are more important than the others are. As a result, delta variance is used to separate the most important features from the rest keeping the classification accuracy as good as possible. Suppose that there are C classes and each class has n training samples in the form of column vectors. The between-class and total matrices of variance are calculated using Eq.(1) and Eq.(2), respectively. Delta variance for a single feature from the feature matrix is calculated using the Eq.(3).

$$VAR_b = \frac{1}{N}\sum_{i=1}^{C}\left(\frac{1}{n}\sum_{j=1}^{n}(a_i^j - \mu_i)\right) * N_i \quad (1)$$

$$where, \quad \mu_i = \frac{1}{n}\sum_{j=1}^{n} a_i^j$$

$$VAR_t = \frac{1}{N}\sum_{j=1}^{N}(a^j - \overline{\mu_N}) \quad (2)$$

$$\nabla VAR = abs(VAR_b - VAR_s) \quad (3)$$

where a_i^j denotes the j-th training sample of the i-th class, μ_i stands for the mean of the i-th class and μ_N represents the mean of all the training samples. N_i is the number of training samples in the i-th class, $N$is the number of total training samples. The values in the '∇VAR' are then sorted in descending order to begin with the top most contributor. The index from this sorted matrix is used to select M number of contributing features, where M is new dimension for the feature matrix. M vs. the classification accuracy is shown in the

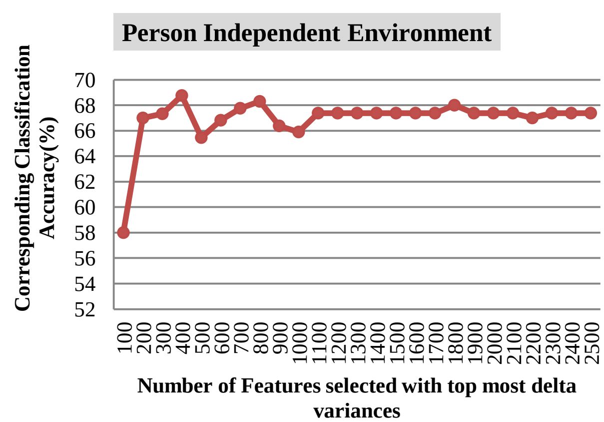

Fig. 4: Number of Features selected with top most delta variances vs. Corresponding Classification Accuracy (%) in Person Independent Environment.

The highest accuracy is achieved by selecting 400 most important features, which is 68.83%.

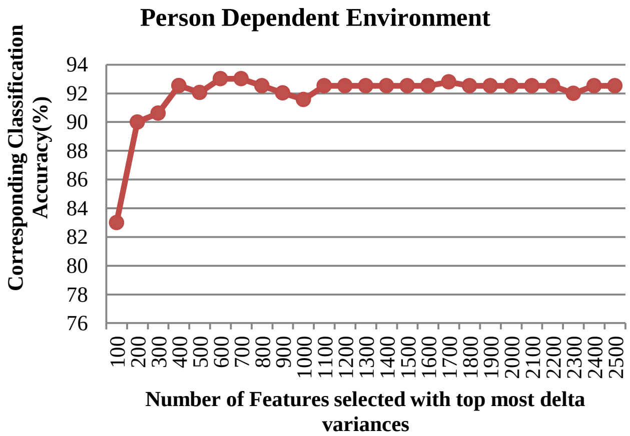

Fig. 5: Number of Features selected with top most delta variances vs. Corresponding Classification Accuracy (%) in Person Dependent Environment.

In the person independent environment, the highest accuracy is achieved by selecting 600 most important features, which is 93.02%. At 400, it achieves 92.6%. Therefore, 400 features are selected for further experiments.

4. Data collection and Experimental setup

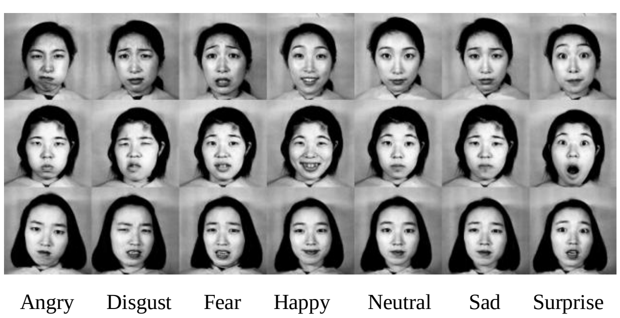

Fig. 6: Sample faces from JAFFE dataset.

A popular and free to use dataset, the Japanese Female Facial Expression (JAFFE) [13] is used for the experiments to evaluate the effectiveness of the proposed method. JAFFE dataset contains 213 images of seven prototype facial expressions (6 basic facial expressions + 1 neutral), posed by 10 Japanese female women. The dataset was planned and assembled by Miyuki Kamachi, Michael Lyons, and Jiro Gyoba [13]. The photos were taken at the psychology department in Kyushu University. The expressions are surprise (30), angry (30), disgust (29), fear (32), happy (31), neutral (30) and sad (31). Same expression from the same subject was collected 2-4 times. All the faces are posed and taken in a controlled environment. Fig. 6 shows some sample faces from JAFFE dataset.

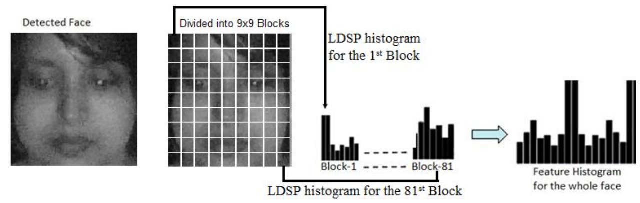

Fig. 7: Facial Feature Extraction

A free online code *fdlibmex* is used library for face detection. The library consists of single *mex* file with a single function. It is an unpublished piece of work. This works not perfectly but well enough for our person independent experiments. The face is then re-dimensioned to 99x99 pixels and equally divided into 9x9=81 blocks of 11x11 pixels each, see Fig. 7. Features are extracted from each block using LDSP. Concatenating feature histograms of all the blocks produces a unique feature vector of 32x81= 2592 dimension for a given image. DR (Dimensionality Reduction) is applied on that feature vector using delta variance. This reduces the feature vector length to 400 from 2592. A non-overlapping ten-fold leave-one subject-out or person independent validation is carried out using multiclass support vector machine LIBSVM [14]. Ten rounds of training and testing are conducted for each subject against the rest nine and the average confusion matrix is reported and compared against the others. The parameter for the LIBSVM to: s=0 for SVM type C-Svc, t=1 for polynomial kernel function, c=1 is the cost of SVM, g=0.0025 is the value of 1/ (length of feature vector), b=1 for probability estimation. LIBSVM is found to be suitable for JAFFE dataset with both six (without neutral) and seven classes of data with these parameter settings. A 10-fold cross validation is also performed using the same parameter setup. Random 90% of the total samples are selected for training and rest 10% is used for testing. Classification accuracy is averaged after doing this for 10 times.

5. Results and Discussion

The method is evaluated on both six-class (without neutral class) and seven-class prototype expression recognition in both person dependent and person independent environment. It is also tested on images with Gaussian white noise to prove its performance consistency in noisy environment. Table 1 and Table 2 show the confusion matrices for LDSP.

Table 1. Confusion Matrix for LDSP (Personin Independent), Classification Accuracy Acieved: 68.8%

	Actual							
	Class	**Angry**	**Disgust**	**Fear**	**Happy**	**Neutral**	**Sad**	**Surprise**
prediction	**Angry**	**83.3**	6.7	0.0	0.0	6.7	3.3	0.0
	Disgust	10.3	**72.4**	3.4	0.0	3.4	6.9	3.4
	Fear	9.4	18.8	**50.0**	6.3	0.0	3.1	12.5
	Happy	0.0	0.0	3.2	**80.6**	3.2	0.0	12.9
	Neutral	6.7	6.7	6.7	3.3	**66.7**	0.0	10.0
	Sad	12.9	6.5	6.5	6.5	6.5	**51.6**	9.7
	Surprise	0.0	0.0	10.0	3.3	10.0	0.0	**76.7**

Table 2. Confusion Matrix for LDSP (Personin Dependent), Classificatio Accuracy Achieved: 92.6%

	Actual							
	Class	**Angry**	**Disgust**	**Fear**	**Happy**	**Neutral**	**Sad**	**Surprise**
prediction	**Angry**	**96.7**	0.0	0.0	0.0	3.3	0.0	0.0
	Disgust	10.3	**89.7**	0.0	0.0	0.0	0.0	0.0
	Fear	0.0	3.1	**84.4**	3.1	0.0	6.3	3.1
	Happy	0.0	0.0	0.0	**96.8**	0.0	3.2	0.0
	Neutral	0.0	0.0	0.0	0.0	**100.0**	0.0	0.0
	Sad	3.2	0.0	3.2	3.2	3.2	**87.1**	0.0
	Surprise	0.0	0.0	3.3	3.3	0.0	0.0	**93.3**

The proposed method is tested against some popular methods e.g., LBP (Local Binary Pattern), LBP_{RI} (Rotation Invariant LBP), LBP_{U2} (Uniform LBP), LBP_{RIU2} (Rotation invariant and Uniform LBP) and LPQ (Local Phase Quantization) [15]. To make the comparison more effective, same experimental setup for all above methods is used except feature selection. Feature selection is used only for LDSP. All the results of Table 3 and Table 4 are obtained using LIBSVM with polynomial, linear and RBF (radial basis function) kernel.

Table 3. Results of LDSP and other popular methods in same experimental setup but different SVM kernel setup . (person dependent)

person dependent	**Classification Accuracy**		
Method	**Linear Kernel**	**Polynomial kernel**	**RBF kernel**
LDSP	*91.31%*	*92.60%*	*91.52%*
LBP	89.72%	90.42%	89.31%
LBP_{RI}	74.17%	74.48%	73.21%
LBP_{U2}	91.43%	92.10%	91.06%
LBP_{RIU2}	73.82%	75.90%	73.12%
LPQ	77.56%	79.56%	78.14%

Experiments are also conducted on 6-class expressions by removing 'natural' class from JAFFE dataset. This is because most of the previous works are done on six expressions class. Therefore, to compare with those results, we have removed one class from the dataset.

Table 4. Results of LDSP and other popular methods in same experimental setup but different SVM kernel setup on JAFFE dataset (person independent)

person independent	**Classification Accuracy**		
Method	**Linear Kernel**	**Polynomial kernel**	**RBF kernel**
LDSP	*67.41%*	*68.83%*	*67.81%*
LBP	62.52%	63.20%	62.82%
LBP_{RI}	44.02%	45.67%	43.11%
LBP_{U2}	59.47%	63.16%	59.89%
LBP_{RIU2}	42.14%	42.80%	41.31%
LPQ	55.27%	56.66%	55.52%

Table 5 shows classification accuracy comparison on 6-class expressions on JAFFE with different SVM kernel.

Table 5. Results of our method and some other popular methods in different SVM kernel setup on 6-class expression.(person dependent)

	Classification Accuracy		
Methods	**Linear Kernel**	**Polynomial Kernel**	**RBF Kernel**
LDSP	*92.8%*	*94.6%*	*92.9%*
Gabor Feature [16]	89.4%	89.4%	89.8%
LBP [17]	91.5%	91.5%	92.6%
LDPv [9] (Local Directional Pattern)	92.8%	92.8%	94.5%

Table 6 shows the accuracy comparison of LDSP with some other methods on JAFFE dataset in person independent environment.

Table 6. Classification accuracy comparison in person dependent environment; (SRC: Sparse Representation-based Classification, GP: Gaussian Process classifier)

Person Independent	**Classification Accuracy**	
Author	Classifier	Classification accuracy
LDSP	*LIBSVM*	*63.12%*
[19]	SVM	58.20%
[20]	SRC	62.38%
[21]	GP	55.00%
[22]	SVM	56.80%

Table 7 shows results comparison in a person dependent environment on JAFFE dataset. A 10-fold cross validation is followed by dividing the dataset into 10 non-overlapping folds with nearly equal number of instances e.g. 21/22 each. One against nine is tested ten times and averaged the results to get the final recognition rate.

To check the performance of the proposed method in a noisy situation, white noise is added to random instances. A 10-fold validation in a person independent environment is carried out to evaluate proposed method against LBP with fixed parameter setup.

Table 7. Comparison of classification accuracy of LDSP+LIBSVM with some other systems on JAFFE dataset in a person dependent experimental environment. (NN: Neural Network, LDA: Local discriminant analysis)

Merhod	Classifier	Classification accuracy
LDSP	*Multi Class SVM(Poly)*	*92.60%*
[23]	SVM	88.09%
[24] *	LDA-based classification	92.00%
[3]	NN	90.10%
[25]	Linear Programming	91.00%

*used a subset of the dataset

Table 8 shows the classification accuracy achieved by proposed method against the others both in noisy and in no noisy environment.

Table 8. Results of LDSP and other popular methods in noisy environment (person independent)

person independent	**Classification Accuracy**	
Method	**No noise**	**With white noise***
LDSP	*68.83%*	*66.58%*
LBP	63.20%	58.27%
LBP_{RI}	45.67%	41.14%
LBP_{U2}	63.16%	59.32%
LBP_{RIU2}	42.80%	40.41%
LPQ	56.66%	48.32%

*Gaussian White noise of 0 mean and 0.001 variance is applied.

Therefore, the above table proves the consistency of LDSP in a noisy environment. The proposed system outperforms all the existing systems almost in all cases according to Table 3-7. 6-class expression gives more accuracy than 7-class expression as there is less space to be confused in 6-class. In JAFFE dataset, pictures are taken in a controlled environment. Still the faces are not straight. The subjects are asked to give expression, therefore it is not natural. Some expressions are ambiguous. Performance will increased if it is applied with automatic alignment.

4. Conclusions

In this paper, a robust and noise insensitive feature descriptor for facial expression recognition is proposed. The method encodes local edge response along with local contrast information for facial expression recognition. Extensive experiments in person dependent, person independent and noisy environment prove that the method is effective and efficient for facial expression recognition. Future work includes study more advanced method for dividing the facial image into sub-images and add weight for those regions. The AdaBoost method presented in [26] serves as a good basis for this research. Motion pictures give more information, which can be added with LDSP.

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