Multi-View Pose and Facial Expression Recognition

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Abstract

Multi-view facial expression recognition is important in many scenarios, as frontal view images are not always available. In this paper, we investigate facial expression recognition from frontal to profile view. Few works have investigated this issue on live captured data. A recent database, multi-pie, allows empirical investigation of facial expression recognition for different yaw angles. Experiments are carried out on 100 subjects over 7 poses for 6 facial expressions (*neutral*, *smile*, *surprise*, *squint*, *disgust* and *scream*). Opencv frontal and profile face detectors are used to locate the face region. Head pose classifiers and pose dependent facial expression classifiers are trained using multi-class support vector machines (SVM). We investigate multi-scale local binary patterns (LBP^{ms}) as well as local gabor binary patterns (LGBP) as texture descriptors.

1 Introduction

The human face is one of the most changeable and complex parts of our body. Thus, the problem of interpreting facial expressions is a complicated one. Factors such as ethnicity, age, facial hair, occlusion, pose and lighting contribute to the difficulty of this problem. Facial expression recognition is a very active research area within the Computer Vision community. This is largely because of its many applications to human-computer interaction systems. Many fields could benefit from accurate facial expression recognition including behavioral science, security, communication and education.

Research in psychology has shown that facial expressions form the major modality in non-verbal human communication. Many facial expression recognition systems have been proposed and accurate results have been reported in constrained settings. See [18] for a review. In general there are two common types of features used for facial expression recognition: geometric based methods and appearance based methods [26]. Geometric features contain information about the location and shape of facial features. Appearance based features examine the appearance change of the face (including wrinkles, bulges and furrows) and are extracted by image filters applied to the face or sub regions of the face. Geometric features are sensitive to noise and tracking errors. Appearance based features are less reliant on initialization and can encode micro patterns in skin texture that are important for facial expression recognition. In this paper we investigate appearance based features.

Psychophysical studies suggest local appearance plays an important role for classification [12]. Variation between facial expressions appear more on some specific regions of the face. Thus, we exploit this finding by adopting local spatial feature histograms by applying a grid over the face region. This approach has previously been demonstrated to provide accurate facial expression recognition [4, 21]. We extend this approach to multi-view facial expression recognition. Previous studies have carried out multi-view facial expression analysis on synthetic data [6, 13]. One of the motivations of this paper is to validate similar experiments on a more challenging live dataset.

The rest of this paper is organized as follows. Background work is presented in section 2. Section 3 outlines how the face region is detected and introduces the local binary pattern (LBP) operator and its extensions LBP^{ms} and LGBP. Section 4 presents the database and results for pose and expression classification. Finally, section 5 presents a discussion of results and conclusions are drawn.

2 Background

Frequently used databases for facial expression recognition typically capture data at near frontal view [8]. High recognition rates for prototypical facial expressions have been recorded for this database, in constrained settings [4, 9, 21]. Pose is one constraint that has largely been unexplored. This is mainly due to a lack of suitable data. Research in psychology has shown how pose can effect a humans ability to perceive facial expressions. Experiments using a Japanese noh mask, show that slight variations in pitch angle changes the two dimensional location of salient facial features which viewers misinterpret as non ridged changes due to muscle action [11]. Psychology experiments have shown that even a 15° head pose change, results in statistically significant changes in how humans perceive emotion [14].

Some effort has been made to investigate into facial expression recognition for large head pose changes [22]. Pantic and Patras [19] explore recognition of facial action units from profile face images sequences. Wang *et al.* [24] show how sensitive 2D facial expression recognition approaches are to head pose variations. This highlights the need to further investigate how head pose effects facial expression classifiers. Other approaches to pose invariant facial expression recognition, learn models of the whole face. These approaches typically do not consider views greater than 45°, when part of the face is occluded [1, 20].

A recent database BU-3DFE [25] has initiated research into multi-view facial expression recognition. Hu *et al.* [7] applied LBPs, histograms of oriented gradients and scale invariant transform features to classify expressions across 5 different head poses, from frontal to profile view. Other similar experiments were carried out by Hu *et al.* [6] with manually labeled facial points and SVMs used for final classification. Conclusions of [6] were that non-frontal views are better than the frontal view for facial expression recognition. Limitations in the work of [7] and [6] are that features are extracted using a set of sparse manually labeled feature points. However it is not obvious how this approach can be applied to live captured data, since some feature points are not visible for large pose variations. Moore and Bowden [13] analyzed appearance based LBP features and LBP variants on the same database. Results from [13] suggest that the frontal view outperforms other views for facial expression recognition contradicting the work of Hu *et al.* One criticism of these approaches is the use of synthetic data. When using the BU-3DFE database, images are re-projected from a 3d textured model for different yaw angles and thus there is less variability in the synthesized dataset than in a live captured dataset.

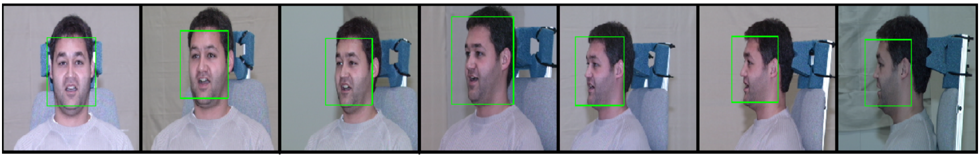

Figure 1: Opencv frontal and profile face detector results

3 Feature Extraction

For a fully automated system we adopt face detectors to find the face region for all poses. LBP features are then extracted for classification. The following section will formulate the use of these features for our experiments. We adopt a dense uniform sampling by extracting histograms from a grid over the face. Face regions are divided into 64 sub blocks aligned over the face.

3.1 Face Detection

The Viola and Jones face detector [23] is used to extract the face region for all poses. This is available from the Opencv library [17]. The face detector uses boosted cascades of harr-like features. The frontal detector was used for poses $0^\circ, 15^\circ$ and 30°. The profile cascade was used for poses 45°, 60°, 75° and 90°. The performance of the frontal detector was superior to the profile detector. Some false positives and missed detections were observed for the profile detector mainly at 75° and 90°. Images that were incorrectly classified were corrected and labeled manually. One parameter which played an important role was the scale factor. A smaller value gives more accurate true positives at the expensive of false positives. False positives were removed manually. Figure 1 shows the results of using the opencv frontal and profile detectors on the multi-pie database.

3.2 Local Binary Patterns

Ojala *et al.* [15] first introduced the LBP operator. Pixels of an image are labeled by thresholding a 3x3 neighborhood with the value of the center pixel and combining the results into a binary number $S(f_p - f_c)$.

$$S(f_p - f_c) = \begin{cases} 1 & \text{if } f_p \geq f_c \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Where f_c is the center pixel and $f_p(p = 0, ..., 7)$ are the pixels surrounding the center pixel. Then, by assigning a binomial factor 2^p for each $S(f_p - f_c)$ the LBP is as follows:

$$LBP = \sum_{p=0}^{7} S(f_p - f_c) 2^p \tag{2}$$

Important properties of LBP features are their tolerance against monotonic illumination changes and their computational simplicity. The LBP operator detects many different texture primitives (spot, line end, edge, corner), typically accumulated into a histogram over a region to capture local texture information.

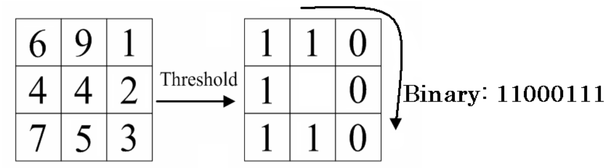

Figure 2: The basic LBP operator

Ojala *et al.* [16] extended this operator to use neighborhoods of different sizes to capture dominant features at different scales. Notation LBP(P,R) denotes a neighborhood of P equally spaced sampling points on a circle of radius R. Figure 2 shows a basic LBP where P = 8 and R = 1. Ojala *et al.* [16] also showed that a small subset of the 2^p patterns accounted for the majority of the texture of images, over 90% of all patterns in the (8,1) neighborhood. These patterns, called uniform patterns (LBP^{u2}), contain at most two bitwise transitions from 0 to 1 or vice versa for a circular binary string. For example 01100000 and 11011111 are uniform patterns. Using uniform patterns for a neighborhood of 8, reduces the histogram from 256 to 59 bins.

3.3 Multi-scale Local Binary Patterns

LBP^{ms} were first introduced by [16]. The LBP^{ms} has been proven to outperform standard LBPs for face recognition [2] and frontal view facial expression recognition [21]. There are two ways to achieve multi-resolution analysis, down sampling the image and applying the LBP operator at a fixed radius, or using a increased radius to sample larger neighborhoods. Here LBP^{ms} is LBP^{u2}(8,R), where R = (1,...,8) is applied to face images to create the LBP^{ms} histogram. LBP^{ms} is formulated below by concatenating histograms from 8 different LBP^{u2} maps to form a single vector.

The histogram h of an image $f(x,y)$ with gray levels in the range $[0, L-1]$ could be defined as

$$h_i = \sum_{x,y} I\{f(x,y) = i\}, i = 0, 1, ..., L-1 \tag{3}$$

where i is the i^{th} gray level,h_i is the number of pixels in the image with gray level i and

$$I(A) = \begin{cases} 1 & if \text{ A is true} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Each LBP^{ms} histogram contains LBP^{u2}(8,R), where R = (1,...,8). Each LBP^{u2}(8,R) map is divided into n regions, $B_0, B_1, ...B_{n-1}$. The histogram of the b^{th} sub block to a specific LBP^{u2}(8,R) map is computed by:

$$H_{R,b} = \left(h_{R,b,0}, h_{R,b,1}, ..., h_{R,b,L-1}\right) \tag{5}$$

where

$$h_{R,b,i} = \sum_{(x,y)} I\left\{LBP^{u2}(8,R)(x,y) = i\right\} \tag{6}$$

Finally, all the histograms pieces computed from all regions of all LBP^{ms} maps are concatenated to a histogram sequence HG, as the final face representation:

$$HG(LBP^{ms}) = (H_{0,0}, ..., H_{0,n-1}, H_{1,0}, ..., H_{7,n-1}) \tag{7}$$

3.4 Local Gabor Binary Patterns

Gabor filters have been shown to be successful when applied to face recognition and facial expression recognition [10]. Gabor filters are effective due to their multi-resolution and multi-orientation decomposition of face images. The combination of gabor and LBPs further enhances the power of the spatial histogram. LGBPs were initially used for face recognition and are impressively insensitive to appearance variations due to lighting and misalignment [27].

To extract LGBPs, the images are convolved with the gabor filters as follows:

$$G(\mu, \nu) = I(x,y) * \psi_{\mu,\nu}(z) \tag{8}$$

where:

$$\psi_{\mu,\nu}(z) = \frac{\left\|k_{\mu,\nu}\right\|^2}{\sigma^2} e^{\frac{-\|k_{\mu,\nu}\|^2\|z\|^2}{2\sigma^2}} \left[e^{ik_{\mu,\nu}z} - e^{\frac{-\sigma^2}{2}}\right] \tag{9}$$

$$k_{\mu,\nu} = k_\nu e^{i\phi_\mu}, k_\nu = 2^{-\frac{\nu+2}{2}}\pi, \phi_{\mu-\mu\frac{\pi}{8}} \tag{10}$$

where μ and ν define the orientation and scale of the gabor filters, $z = (x,y)$ and $\|\cdot\|$ denotes the norm operator. Five scales are used $\nu \in \{0,...4\}$ and eight orientations $\mu \in \{0,...,7\}$

In LGBP, there are 40 gabor magnitude maps and each map is divided into 64 sub blocks. The overall representation of the LGBP is computed similar to LBP^{ms} where:

$$HG(LGBP) = \left(H_{0,0,0}, ..., H_{\mu,\nu,i,}, ..., H_{4,7,63}\right) \tag{11}$$

4 Experiments

4.1 Multi-Pie

The multi-pie database [5] contains images from 339 subjects. Subjects are predominantly male (70%). 60% of subjects were European Americans, 35% Asian and 3% African Americans. The average age of the subjects was 28 years old. Data was captured during four sessions over a six month period. In each session, subjects were instructed to display various facial expressions (*neutral*, *smile*, *surprise*, *squint*, *disgust* and *scream*). Before each session subjects were shown examples of the particular facial expression from the Cohn-Kanade database [8]. Thirteen cameras were located at head height in 15 intervals.

For our experiments we consider only 7 different poses (0°, 15°, 30°, 45°, 60°, 75° and 90° yaw angles), see figure 1. 100 subjects were selected so that all subjects were present at all four sessions and thus for each subject all expressions were available. In total 4,200 images were used for our experiments. Images were resized to 320 x 240, where the typical face detection size was around 100 x 100 pixels. To test the algorithms generalization performance, all experiments in the following sections are based on 10 fold cross validation.

Training and test sets were divided 80-20%. This 20% testing data is taken from subjects that were not present in the training data. This ensures that any features extracted for classification provide person independent facial expression recognition.

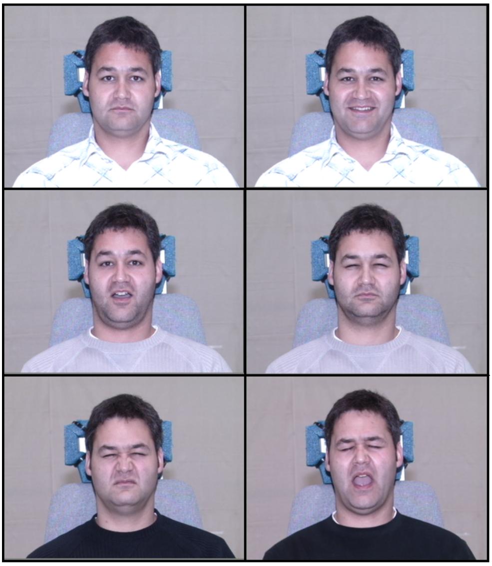

Figure 3: Example of facial expressions from multi-pie database. Top row = expressions neutral and smile. Middle row = expressions surprise and squint. Bottom row = expressions disgust and scream

4.2 Head Pose and Facial Expression Classification

To classify pose and expression we adopt a cascade approach where the classification task is divided into two steps. First we use a pose classifier trained over 7 views from frontal to profile view in 15° increments. Secondly we use a pose dependent expression classifier to classify expressions. When training the pose classifiers all expressions for each pose are including in the training sets. Thus the difference between expressions is regarded as within-class variance. Expression classifiers are trained for each pose. In total 42 expression classifiers are trained.

An SVM classifier is adopted since it is a well understood classification technique that has been demonstrated to be effective for facial expression recognition. An SVM takes a feature vector as input in an n-dimensional space and constructs a separating hyperplane in that space, one which will maximize the margin between the positive and negative sets. The better the hyperplane, the larger the distance to the neighboring points from both classes. SVMs are usually binary classifiers, here we used a multi class SVM [3] which uses a one against all approach. Given the large dimensionality of the feature vectors produced in section 3, a linear kernel is used to reduce the training times. Results reported in section 4.3 are the best results, optimized for the dataset.

4.3 Results

Table 1 shows the overall results for head pose and facial expression classification. As expected, LGBP outperformed LBP^{ms} for both head pose and facial expressions. Both features achieved recognition results of over 99% averaged over 7 poses. LGBP significantly outperforms LBP^{ms} by over 6% for facial expressions over all poses. This performance increase may well be attributed to the multi-orientation analysis present in the LGBP features. Table 2 shows results of both features for each head pose. Surprisingly, results at angles 15° and 60° outperform frontal view. View 15°, achieves the best results for both features. Another interesting finding for both features is profile views outperform other views, where more of the face is visable. Given some of the problems with occlusion for profile view (discussed in the next section), this result is interesting.

Features	Pose	Expressions
LBP^{ms}	99.13	73.98
LGBP	**99.45**	**80.17**

Table 1: Recognition rates for head pose and overall facial expression recognition on multi-pie database

	0	15	30	45	60	75	90
LBP^{ms}	76.7	**80.5**	70.3	69	78.6	63	73.8
LGBP	82.1	**87.3**	75.6	77.8	85	71	75.9

Table 2: Facial expression recognition results for each yaw angle

Tables 3 and 4 show the confusion matrices for LBP^{ms} and LGBP respectively. In general, the same patterns can be seen for both sets of features. The most confusion occurs between expressions *squint* and *disgust*, due to the expressions having similar deformation around the eyes. In fact, the *squint* expression has some confusion with other expressions including *neutral* and *smile*. This is most likely due to the fact that *squint* is a relatively subtle expression and thus is hard to disambiguate between other expressions. Subtle expressions are hard to distinguish because of the variability across subjects. More confusion is present between expressions *scream* and *surprise*, this can be attributed to the similar deformation of the mouth. *Surprise* usually is associated with raised eyebrows, but for some subjects in this database no noticeable deformation occurs around the eyebrows. This could contribute to the confusion. However, the best performing expression for both features are *surprise* and *scream*. These expressions have lots of deformation and thus are easier to distinguish than more subtle expressions.

5 Discussions and Conclusions

The multi-pie dataset is a very challenging dataset. Figure 4 shows examples of some of these difficulties. Of the 100 subjects used for our experiments, 49 subjects wore glasses in some or all recording sessions. Implications of this are significant given that at different head poses glasses can occlude parts of the eyes and eyebrows, where subtle information can be lost. Other challenging aspects of this dataset are hair covering the eyes and eyebrows for

	Neu	Smi	Sur	Squ	Dis	Scr
Neu	**73.92**	11.57	2.98	8.91	3.41	0.66
Smi	9.21	**78.04**	4.04	4.79	3.62	1.74
Sur	3.41	3.40	**81.01**	2.54	1.89	9.21
Squ	9.28	8.84	2.90	**60.11**	18.71	1.60
Dis	5.51	4.85	1.74	14.87	**69.21**	5.27
Scr	0.15	1.15	12.95	0.94	3.48	**81.57**

Table 3: Confusion matrix for facial expressions over all yaw angles for LBP^{ms} features

	Neu	Smi	Sur	Squ	Dis	Scr
Neu	**80.55**	8.02	2.75	6.87	2.67	0.58
Smi	7.54	**82.74**	2.61	5.07	2.62	0.87
Sur	1.03	3.55	**88.67**	0.87	1.81	5.52
Squ	8.61	7.45	1.37	**66.26**	16.89	0.87
Dis	4.12	3.55	1.02	14.70	**74.81**	3.25
Scr	0.14	0.94	8.52	0.36	2.18	**88**

Table 4: Confusion matrix for facial expressions over all yaw angles for LGBP features

some views. The second and third rows in figure 4 show how hair can occlude facial features for views 60°, 75° and 90°. This database also has subjects with beards and mustaches. Other popular databases (including JAFFE and Cohn-Kanade database [8]) do not have the same level of variability.

The area captured by the face detectors include some background (see figure 1). In the frontal view the background includes some of the chair. Also for profile view the background in the face region is slightly different to the background from poses 15°-75°. Thus, when training the head pose classifiers the background is different for different views so some background features could be learnt. However for the facial expression classifiers the background is consistent thus forcing the SVM to select features which discriminate between facial expressions, which is the main focus of the paper.

Another variable to consider when evaluating the above results is the noise included by the face detector. This noise is more apparent for the profile detector, particularly at 75° and 90° views. These variations in the dataset are probably a contributing factor as to why results for the multi-pie database are not as high as results reported for other databases (JAFFE and Cohn-Kanade). However, given the complexity of the dataset, the results are surprisingly high.

Gross *et al*. evaluated facial expression recognition for frontal view on the multi-pie database, with results of under 50% [5]. A direct comparision with our work is unfair as the number of subjects used for training and testing was small. It should also be noted that these experiments were carried out to evaluate the effect of illumination on expression recognition and not to find peak expression recognition performance.

In our experiments, results at angles 15° and 60° outperformed all other views. This contradicts a previous study with appearance based features where frontal view was optimal [13]. Further still, other studies have suggested that 45° is the optimal view for facial expression recognition [6]. In summary and observing results in table 2, experiments suggest that facial expression recognition is largely consistent across all poses, but the optimal view

Figure 4: Examples of difficult subjects in the multi-pie database

is subject to the data and features used.

This paper presents an investigation into head pose and multi view facial expression recognition on a challenging dataset. Face detection for head poses from frontal to profile view was performed using an opencv implementation of the Viola and Jones face detector. Local spatial histograms of LBP^{ms} and LGBP features were evaluated. Multi-class SVM's were used for classification of head pose and facial expressions. Results of over 99% were achieved for head pose classification. LGBP outperformed LBP^{ms} by over 6% for facial expression recognition. Expressions *surprise* and *scream* achieved over 88% recognition accuracy using the LGBP features. Deviation in pitch and roll angles of the subjects head and inherent noise in the face detector show the tolerance of this approach to such variations.

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