The effects of Pose on Facial Expression Recognition

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Abstract

Research into facial expression recognition has predominantly been based upon near frontal view data. However, a recent 3D facial expression database (BU-3DFE database) has allowed empirical investigation of facial expression recognition across pose. In this paper, we investigate the effects of pose from frontal to profile view on facial expression recognition. Experiments are carried out on 100 subjects with 5 yaw angles over 6 prototypical expressions. Expressions have 4 levels of intensity from subtle to exaggerated. We evaluate features such as local binary patterns (LBPs) as well as various extensions of LBPs. In addition, a novel approach to facial expression recognition is proposed using local gabor binary patterns (LGBPs). Multi class support vector machines (SVMs) are used for classification. We investigate the effects of image resolution and pose on facial expression classification using a variety of different features.

1 Introduction

Facial expression recognition is a very active research area due to its importance in both human computer and social interaction. Many fields benefit from accurate facial expression recognition including behavioral science, security, communication and education. The aim of this paper is to investigate the effects of pose on facial expression classification.

Psychological studies indicate a correlation between base emotions and facial expression across all cultures [3]. This is reflected by current approaches to facial expression recognition, that classify a set of prototypical emotions such as *joy*, *sadness*, *anger*, *disgust*, *surprise* and *fear* [5, 9, 13]. Many methods for the classification of these prototypical expressions have been presented. There are two common approaches: geometric feature based methods and appearance based methods [21]. Geometric features deal with the shape and location of facial components. Appearance based features utilize 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 usually require reliable and accurate facial feature detection and tracking. However, appearance based features are less reliant on initialization, do not suffer from tracking errors, and can encode changes in skin texture that are important for facial expression recognition. In this paper we investigate appearance based features.

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Psychophysical studies in saccadic eye movements [12] indicate that local appearance is important for classification. People can recognize objects when they seek regions where discriminating information is located. Our approach utilizes this finding by dividing face images into sub blocks and comparing the similarities between these sub blocks. This is a proven method for accurate facial expression recognition [5, 18].

Frequently used databases typically capture frontal view data, as a result, most of the existing efforts to classify facial expressions focus on near frontal view data. A recent database BU-3DEF [20] which consists of 3D range data motivates us to investigate the effects of pose change on facial expression recognition. We attempt to classify each of the prototypical expressions at 5 different yaw angles (0,30,45,60,90). LBPs have yielded accurate results with face recognition [6] and more recently with frontal facial expressions [4, 5, 9, 23]. We apply the LBP operator and its variants to the BU-3DEF database and present our findings. Also we investigate a novel approach to facial expression recognition using local gabor binary patterns (LGBPs). A SVM is adopted for classification as they are well founded in statistical learning theory and have been successfully applied to head pose estimation [14] and facial expression recognition [11].

The rest of this paper is organized as follows. Related work is presented in section 2. Section 3 introduces the LBP operator and its extensions. Also in section 3 we formulate the use of LGBPs for facial expression recognition. Section 4 presents the database and the different yaw angles used in our experiments. Also experiments, results and a discussion of the effects of pose on facial expression are presented in section 4. Finally conclusions are drawn in section 5.

2 Related Work

Research into facial expression recognition has predominantly been based on near frontal view data [5, 9, 18]. High recognition rates for these prototypical facial expressions have been recorded in constrained settings. However, the ultimate goal should be facial expression recognition in less constrained, real-life scenarios. Pose is one constraint that therefore requires further investigation.

Pantic and Patras [17] explore automatic recognition of facial action units from profile face view image sequences. Wang et al. [19] analyzed the effect of view tolerance on a frontal view trained facial expression classifier. Results showed the need for further investigation into the effects of pose on facial expression classifiers.

More recently two studies have explored facial expression recognition with varying yaw angles on the BU-3DEF database [7, 8]. Hu et al. [8] focuses on facial expression recognition using LBPs, Histograms of Oriented Gradients (HOGs) and the Scale Invariant Feature Transform (SIFT) to characterize facial expressions over 5 yaw rotation angles from frontal to profile views. Other contributions of this work are the strong performance increase when features are combined with Locality Preserving Projection (LPP). In [7], Hu et al. utilize the geometric 2D displacement of manually labeled facial points, and concatenates them together to form a feature vector as input to a SVM classifier. The main conclusion of [7] is that non-frontal views are better than frontal view for a computer to recognize facial expressions. As this contradicts many previous studies, an interesting question is if this conclusion is related to the geometric features used. In this paper, we explore this question using an appearance based approach. Noticeable limitations in the work of [8] and [7] are that features are extracted using a set of sparse manually labeled feature points. We adopt a dense

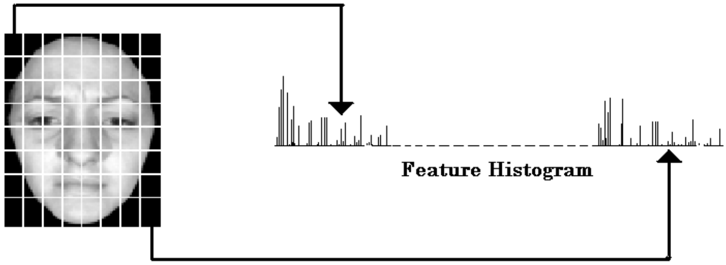

Figure 1: Face image is divided into sub blocks from which features are extracted and concatenated into a single spatial histogram

uniform sampling and use a SVM to select relevant features.

3 Features

Several different features have been applied to the area of facial expression recognition with success. However, most of these have been applied to frontal view only. In this paper we investigate the influence of pose on several different feature sets for expression recognition. We use an appearance based approach by dividing images into 64 sub blocks coarsely aligned over the face (see Figure 1). Feature vectors contain concatenated feature histograms built from each sub block.

3.1 Local Binary Patterns (LBPs)

The LBP operator was first introduced by Ojala et al [15]. The operator labels the pixels $f_p(p = 0,...,7)$ of an image by thresholding a 3x3 neighborhood of each pixel with the value of the center pixel f_c and considering the result as a binary number $S(f_p - f_c)$

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

Then, by assigning a binomial factor 2^p for each $S(f_p - f_c)$ the LBP is as follows

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

Over a region, LBPs are accumulated in a histogram and the concatenation of these neighborhoods are then used as a descriptor. This characterizes the spatial structure of the local image texture. The most 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.

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

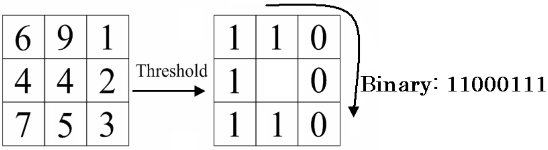

Figure 2: The basic LBP operator

= 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, contain at most two bitwise transitions from 0 to 1 or vice vera 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.

Other extensions of the LBP operator used in this paper are rotation invariant LBPs (LBP^{ri}) and rotation invariant uniform LBPs (LBP^{riU2}) [16]. To remove the effect of rotation i.e. to assign a unique identifier to each rotationally invariant LBP:

$$LBP^{ri}_{P,R} = min\{ROR(LBP_{P,R}, i)|i = 0, 1, ..., P-1\} \tag{3}$$

Where $ROR(x,i)$ performs a circular bit-wise right shift on the P-bit number x, i times. This operation further reduces the histogram, e.g. $P = 8$ LBP^{ri} has 36 unique rotational invariant patterns. The concept of uniform patterns can be extended to this feature, also reducing the number of bins from 36 to 9. This provides uniform rotational invariant local binary patterns LBP^{riu2}.

To further characterize the image information, the LBP operator is applied to the gradient magnitude image (LBP^{gm}). The gradient at each pixel in the image is defined as: $\nabla m = (\frac{\partial m}{\partial x}, \frac{\partial m}{\partial y})^T$. Sobel gradient filters are adopted for the horizontal and vertical derivative filters. This approach is a derivative based LBP which encodes the velocity of local variation. Similar features have been successfully applied to facial expressions recognition [9].

All features mentioned above can be concatenation into a single feature vector HG for image LBP^{xxx}, with n sub blocks:

$$HG(LBP^{xxx}) = (H_0, H_1, ..., H_{n-1}) \tag{4}$$

where the histogram of the r^{th} sub block of LBP^{xxx} is computed by:

$$H_r = (h_{r,0}, h_{r,1}, ..., h_{r,u-1}) \tag{5}$$

where u is the total number of bins for feature LBP^{xxx} and h is defined as:

$$h_i = \sum_{x,y} I\{LBP^{xxx}(x, y = i)\}, i = 0, 1, ..., u-1 \tag{6}$$

where i is the i^{th} bin of histogram h, h_i is the number of patterns in the image with LBP^{xxx} pattern i and

$$I(A) = \begin{cases} 1 & if \text{A is true} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

3.2 Multiscale Local Binary Patterns (LBP^{ms})

Multi resolution analysis can be achieved by using different values of P and R. The LBP^{ms} has been proven to outperform standard LBPs for face recognition [1] and frontal view facial expression recognition [18]. Here LBP^{ms} is LBP^{u2}(8,R), where R = (1,...,8) is applied to face images to extract the LBP^{ms} histogram. LBP^{ms} is formulated in the same way as other features in section 3.1. However the final vector will concatenate 8 different LBP^{u2} maps:

$$HG(LBP^{ms}) = (H_{0,0},\ldots,H_{0,n-1},H_{1,0},\ldots,H_{7,n-1}) \tag{8}$$

3.3 Local Gabor Binary Patterns (LGBPs)

Gabor filters have been successfully applied to facial expression recognition [10]. Gabor wavelets have been shown to be suitable for image decomposition and representation when the goal is the derivation of local and discriminative features. The combination of gabor and LBPs further enhances the power of the spatial histogram, and exploits multi-resolution and multi-orientation gabor decomposition. LGBPs were initially used for face recognition [22]. LGBPs are impressively insensitive to appearance variations due to lighting and misalignment [22]. To our knowledge, LGBPs have not been investigated as a feature for facial expression recognition.

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

$$G(\mu,\nu) = I(x,y) * \psi_{\mu,\nu}(z) \tag{9}$$

where:

$$\psi_{\mu,\nu}(z) = \frac{\left\|k_{\mu,\nu}\right\|^2}{\sigma^2} e^{\frac{-\|k_{\mu,\nu}\|^2\|z\|^2}{2\sigma^2}} \left[e^{ik_{\mu,\nu}z} - e^{\frac{-\sigma^2}{2}}\right] \tag{10}$$

$$k_{\mu,\nu} = k_\nu e^{i\phi_\mu}, k_\nu = 2^{-\frac{\nu+2}{2}}\pi, \phi_{\mu-\mu\frac{\pi}{8}} \tag{11}$$

where μ and ν define the orientation and scale of the gabor filters, $z = (x,y)$ and $\|\cdot\|$ denotes the norm operator. Two scales are used $\nu \in \{0,1\}$ and eight orientations $\mu \in \{0,\ldots,7\}$

In LGBP, there are 16 gabor magnitude maps and each map is divided into 64 sub blocks. The overall representation of the LGBP:

$$HG(LGBP) = \left(H_{0,0,0},\ldots,H_{\mu,\nu,i,},\ldots,H_{1,7,63}\right) \tag{12}$$

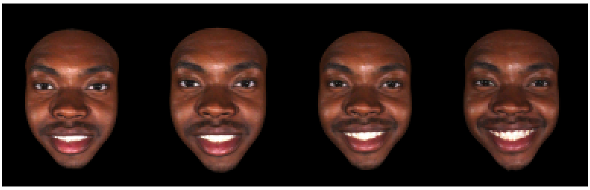

Figure 3: Examples of *joy* expression, left to right intensity 1 to 4

4 Experiments

4.1 BU-3DFE database

Most facial expression databases available are frontal view only, the BU-3DEF database [20] provides 3D textured models of six prototypical facial expressions, from which we can investigate the effects of pose by extracting projected 2D images at different yaw angles. In the BU-3DEF database, there are 100 subjects, including undergraduates, graduates and faculty from the State University of New York Binghamton. The database consists of 60% female and 40% male with a variety of ethnicity. Every subject performs each of the six prototypical expressions as well as neutral. Each expression is captured at four different intensity levels (see figure 3).

4.2 Classification

In our experiments, we attempt to classify each of the prototypical expressions at 5 different yaw angles (0,30,45,60,90), this is the same data used in [7] allowing comparison of results. A SVM classifier is adopted here since it is a well understood classification technique that has been demonstrated to be effective in facial expression recognition. A 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. Two hyperplanes are constructed on either side of the separating hyperplane. The better the hyperplane, the larger the distance to the neighboring points from both classes. SVMs are usually binary classifiers, here we used SVM multi class [2] which uses a one against all approach to solve the 6-class problem. All results on the BU-3DEF database are done with 10 fold cross validation. We use training sets of 90 subjects and test sets of 10 subjects. In an attempt to classify pose and expression we use a sequential approach. First we use a pose classifier trained on 5 different views, secondly we train view dependent expression classifiers. Our experiments achieve 100% success rate for pose estimation over the 5 yaw angles for all features. This is due to the difference in yaw angle being significant (between 15° and 30°) . However the main aim of this paper is to investigate the effects of pose on facial expression recognition.

4.3 Results

Table 1 shows the overall recognition results of features over 4 resolutions. Interestingly, there is no significant perform increase for higher resolution, as in general it is the faces macro features which represent deformation. Features LBP^{ri} and LPB^{riu2} perform poorly on facial expressions. This is most likely because the histograms are not descriptive enough to disambiguate facial expressions correctly. Interestingly LBP^{gm} performed worse than LBP^{u2}. Thus the derivative based LBP^{gm}, which encodes velocity of local variation is poorer than the standard LBP^{u2} on raw image data for classifying facial expressions. LBP^{ms} outperforms standard LBP^{u2} by up to 8% utilizing the multi resolution analysis. *LGBPs* outperforms all other features. *LGBPs* perform better because of multi resolution analysis combined with multi orientation analysis. Table 2 and table 3 show confusion matrices for the best performing features, LBP^{ms} and LGBPs respectively. LGBPs outperform LBP^{ms} for all expressions except *disgust*, where results are similiar. The largest confusion occurs between expressions *anger* and *sadness* for both sets of features. Also confusion for expressions *disgust* and

Feature	32x44	44x62	64x88	80x110
Lbp^{riu2}	**47.28**	46.12	46.31	46.32
Lbp^{ri}	**47.53**	46.28	45.93	46.56
LBP^{gm}	52.91	51.49	53.2	**53.29**
LBP^{u2}	**58.44**	57.33	57.12	56.24
LBP^{ms}	62.41	62.9	64.98	**65.02**
LGBP	66.76	67.84	**67.96**	66.79

Table 1: Performance of features for 4 different resolutions

Feature	Anger	Disgust	Fear	Joy	Sadness	Surprise
Anger	**55.31**	15.31	4.94	1.31	19.87	3.25
Disgust	12	**63.31**	7.06	4.50	7.56	5.56
Fear	6.50	9.25	**49**	12.19	11.06	12
Joy	3.37	6.25	9.31	**76.94**	1.06	3.06
Sadness	15.75	7.37	6.31	3.13	**63.38**	4.06
Surprise	2.81	5.63	3.38	2.50	3.50	**82.19**

Table 2: Confusion matrix for LBP^{ms}

anger is evident in both table 2 and table 3. This is common in facial expression recognition as both expression are hard to distinguish. *Surprise* is the best classified facial expression for both LBP^{ms} and LGBPs, while *fear* performs poorest for both features.

Hu et al [7] presented evidence that non frontal views are best for automatic recognition of facial expressions over varying yaw angles. However, as can be seen, figure 4 shows conflicting results. Frontal pose is the optimal view over all resolutions for features *LGBP*, LBP^{ms} and LBP^{u2}. These features are the 3 best for facial expression classification (see table 1) in our experiments. However, from figure 4, it is also evident that performance does not decrease significantly due to yaw variation. Also from figure 4, we can observe that weaker features sometimes perform better at non frontal views, but even in this scenario, the optimal yaw angle varies. This provides evidence that selection of features, plays an important role in answering the question which view is optimal for facial expression recognition. Weaker features might not be efficient enough to utilize the discriminatory information available at frontal pose.

Another important question is how does yaw variation effect individual expression recognition performance. Figure 5 shows the performance of each expression over 5 yaw angles for LBP^{u2}, LBP^{ms} and LGBPs over 4 resolutions. It does not follow that because frontal

Feature	Anger	Disgust	Fear	Joy	Sadness	Surprise
Anger	**63.06**	8.81	3.50	1.88	19.62	3.13
Disgust	14.75	**63.25**	6.63	5.75	6.44	3.19
Fear	6.12	9.38	**50.94**	14.06	10.19	9.31
Joy	2.56	4.81	10.37	**79**	1.69	1.56
Sadness	17.56	2.81	5.88	1.44	**68.13**	4.19
Surprise	1.31	4.69	5.50	1.56	3.56	**83.37**

Table 3: Confusion matrix for LGBPs

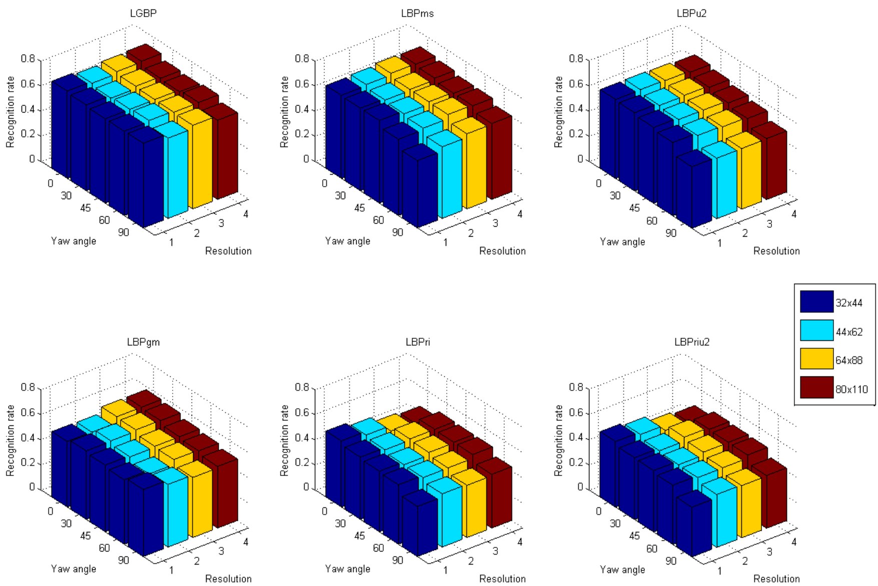

Figure 4: Recognition rate of view independent classifiers for all expressions

view is optimal for overall expression recognition, that individual expressions are optimal at frontal view. This is confirmed by figure 5. *Sadness* performs remarkably well at profile view (yaw 90) over all three features, often outperforming other views. For the LGBP feature over all 4 resolutions, *sadness* is consistently classified best at non frontal view. Another interesting finding is the performance drop of the expression *joy* as the yaw angles increases for the LGBP feature. This suggests that important discriminatory information is lost as the yaw angle increases for the *joy* expression. This finding is only evident for LGBPs and not the other features, suggesting that complementary information between different features exists. Also, from these results it is clear that LBP^{u2} suffers because of its inability to classify the expressions of *anger* and *fear*.

An overall performance of 71.1% was achieved for a combined feature vector of LGBPs and LBP^{ms}. It is evident from figure 5 that complimentary information is present in both LGBPs and LBP^{ms} due to different performance at different yaw angles. Combining the feature vectors together as input to a SVM, gives a performance increase of just over 3%. Table 4 shows a comparison of geometric and appearance feature based approaches. Both approaches use a SVM as the classifier and are tested on similiar yaw variations. However the geometric based method [7] requires manually labeled feature points of the mouth, eyes and eyebrows.

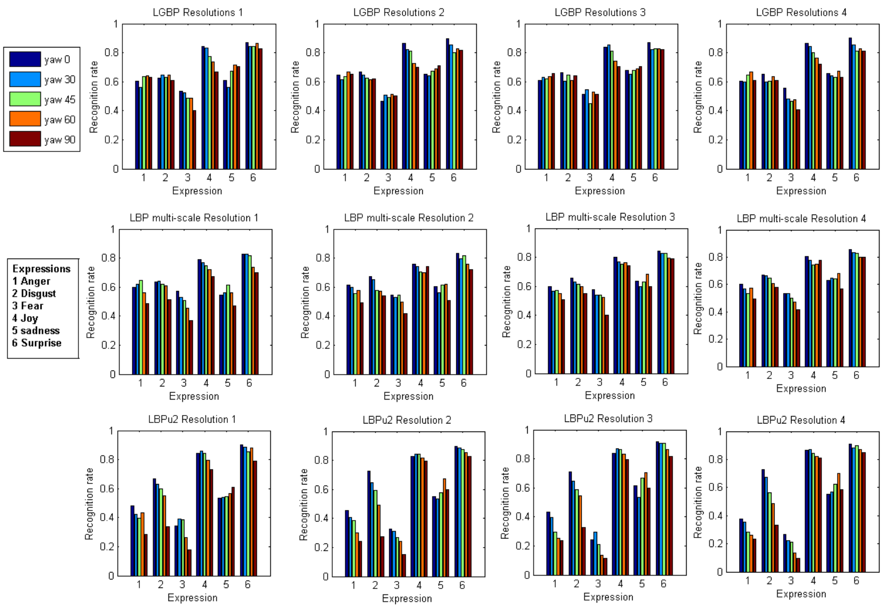

Figure 5: Performance of individual expressions for each yaw angle

Feature method	Results
Geometric based [7]	66.5
LGBP/LBP^{ms}	71.10

Table 4: Comparison of features methods

5 Conclusions

The effects of pose on facial expression recognition is a largely unexplored area. Robust facial expression recognition systems must have the ability to classify expressions from different poses. This paper investigates the effects of pose on facial expression recognition using variations of LBPs at different resolutions. We have shown that *LGBPs* outperform other features. *LGBPs* utilize multi-resolution spatial histograms combined with local intensity distributions and spatial information. Our results also show the strong performance of LBP^{ms} and when combined with *LGBPs*, a recognition rate of 71.1% is achieved. Our results show that frontal pose is optimal for facial expression recognition, however this is dependent on feature selection. Weaker features performed better at non frontal pose. We investigated how individual expressions performed over a range of poses. We also found that some expressions performed better at non frontal views.

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