A Novel Method of Face Recognition Using Lbp, Ltp And Gabor Features

Koneru. Anuradha, Manoj Kumar Tyagi

Abstract:- Face recognition has received a great deal of attention from the scientific and industrial communities over the past several decades owing to its wide range of applications in information security and access control, law enforcement, surveillance and more generally image understanding. In this paper we combine KLDA(combination of LBP and GABOR features) with gradient face features(which are more resistive to the noise effects) for more effective recognition process. Specifically, we make three main contributions: (i) we present a simple and efficient preprocessing chain that eliminates most of the effects of changing illumination while still preserving the essential appearance details that are needed for recognition; (ii) we introduce Local Ternary Patterns (LTP), a generalization of the Local Binary Pattern (LBP) local texture descriptor that is more discriminant and less sensitive to noise in uniform regions, and we show that replacing comparisons based on local spatial histograms with a distance transform based similarity metric further improves the performance of LBP/LTP based face recognition; and (iii) we further improve robustness by adding Kernel PCA feature extraction and incorporating rich local appearance cues from two complementary sources – Gabor wavelets and LBP – showing that the combination is considerably more accurate than either feature set alone.

Keywords– Face recognition, illumination invariance, image preprocessing, kernel principal components analysis, local binary patterns, visual features.

1.INTRODUCTION

Within the past decade, major advances have occurred in face recognition. Many methods have been proposed for face recognition . However, the performance of most existing face recognition methods is highly sensitive to illumination variation. It will be seriously degraded if the training/testing faces under variable lighting. Thus, illumination variation is one of the most significant factor affecting the performance of face recognition and has received much attention in recent years. Many methods have been proposed to handle the illumination problem. In general, these methods can be divided into three main categories. The first approach uses image processing technique/model to normalize ace images under different illumination conditions. For instance, histogram equalization (HE) ,logarithm transform are widely used for illumination normalization. However, it is difficult for these image processing techniques to account for different lighting conditions. There have been models developed to remove lighting effects from images under illumination conditions. In this paper we combine LBP, LTP patterns GABOR FEATURES and GRADIENT FACE features for face recognition purpose under difficult varying lighting conditions.

1. Gradient faces is insensitive to illumination changes and can effectively deal with face recognition under different. Gradient faces is more robust to different illumination, including uncontrolled (natural) lighting conditions.

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2. Gradient faces is extracted from the gradient domain; thus, it has the advantage of the gradient domain. Compared with pixel domain, the gradient domain considers the relationships between the neighboring pixel points such that the gradient domain is able to reveal underlying inherent structure of image data.

2.METHODOLOGY

Making recognition more reliable under uncontrolled lighting conditions is one of the most important challenges for practical face recognition systems. We tackle this by combining the strengths of robust illumination normalization, local texture based face representations, and distance transform based matching, kernel-based feature extraction and multiple feature fusion.

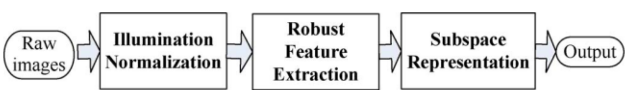


Fig.1. Stages of Full Face Recognition Method

The proposed face recognision system consists of image normalization, feature extraction and subspace representation. Each stage increases resistance to illumination variations and makes the information needed for recognition more manifest. The method centres on a rich set of robust visual features that is selected to capture as much as possible of the available information. A well-designed image preprocessing pipeline is prepended to further enhance robustness. The features are used to construct illumination-insensitive subspaces, thus capturing the residual statistics of the data with relatively few training samples. We will investigate several aspects of this framework:

1) The relationship between image normalization and feature sets. Normalization is known to improve the performance of simple subspace methods (e.g. PCA) or classifiers (e.g. nearest neighbors) based on image pixel representations, but its influence on more sophisticated feature sets has not received the attention that it deserves. A given preprocessing method may or may not improve the performance of a given feature set on a given data set. For example, for Histogram of Oriented Gradient features combining normalization and robust features is useful, while histogram equalization has essentially no effect on LBP descriptors, and in some cases preprocessing actually hurts performance – presumably because it removes too much useful information. Here we propose a simple image preprocessing chain that appears to work well for a wide range visual feature sets, eliminating many of the effects of changing illumination while still preserving most of the appearance details needed for recognition.

2) Robust feature sets and feature comparison strategies. Current feature sets offer quite good performance under illumination variations but there is still room for improvement. For example, LBP[2] features are known to be sensitive to noise in near-uniform image regions such as cheeks and foreheads. We introduce a generalization of LBP called Local Ternary Patterns (LTP) that is more discriminant and less sensitive to noise in uniform regions. Moreover, in order to increase robustness to spatial deformations, LBP based representations typically subdivide the face into a regular grid and compare histograms of LBP[4] codes within each region. This is somewhat arbitrary and it is likely to give rise to both aliasing and loss of spatial resolution. We show that replacing histogramming with a similarity metric based on local distance transforms further improves the performance of LBP/LTP based face recognition.

3) Fusion of multiple feature sets. Many current pattern recognition systems use only one type of feature. However in complex tasks such as face recognition, it is often the case that no single class of features is rich enough to capture all of the available information. Finding and combining complementary feature sets has thus become an active research topic, with successful applications in many challenging tasks including handwritten character recognition and face recognition. Here we show that combining two of the most successful local face representations, Gabor wavelets and Local Binary Patterns (LBP), gives considerably better performance than either alone. The two feature sets are complimentary in the sense that LBP captures small appearance details while Gabor wavelets encode facial shape over a broader range of scales.

3.2 LOCAL TERNARY PATTERNS

3.2.1 Local Binary Patterns (LBP):

Ojala introduced Local Binary Patterns (LBP) as a means of summarizing local gray-level structure. The LBP operator takes a local neighborhood around each pixel, thresholds the pixels of the neighborhood at the value of the central pixel and uses the resulting binary-valued image patch as a local image descriptor. It was originally defined for 3×3 neighborhoods, giving 8 bit integer LBP codes based on the 8 pixels around the central one. Formally, the LBP operator takes the form

$$LBP(x_c, y_c) = \sum_{n=0}^{7} 2^n \, s(i_n - i_c)$$

where in this case *n* runs over the 8 neighbors of the central pixel *c*, *ic* and *in* are the gray-level values at *c* and *n*, and *s*(*u*) is 1 if *u*≥ 0 and 0 otherwise. The LBP encoding process is illustrated in Fig. 2.

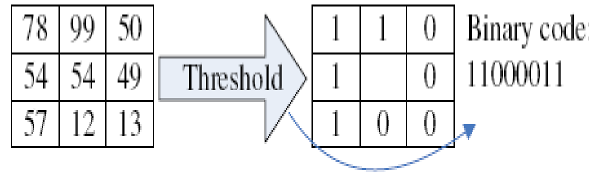


Fig2. Illustration of the basic LBP operator

The first defined LBP's for neighborhoods of different sizes, thus making it feasible to deal with textures at different scales. The second defined the so-called *uniform patterns*: an LBP is 'uniform' if it contains at most one 0-1 and one 1-0 transition when viewed as a circular bit string. For example, the LBP code in Fig. 2is uniform. Uniformity is important because it characterizes the patches that contain primitive structural information such as edges and corners. Ojala observed that although only 58 of the 256 8-bit patterns are uniform, nearly 90 percent of all observed image neighbourhoods are uniform and many of the remaining ones contain essentially noise. Thus, when histogramming LBP's the number of bins can be reduced significantly by assigning all non-uniform patterns to a single bin, typically without losing too much information.

3.2.2 Local Ternary Patterns (LTP)

LBP's have proven to be highly discriminative features for texture classification and they are resistant to lighting effects in the sense that they are invariant to monotonic gray-level transformations. However because they threshold at exactly the value of the central pixel *ic* they tend to be sensitive to noise, particularly in near-uniform image regions, and to smooth weak illumination gradients. Many facial regions are relatively uniform and it is legitimate to investigate whether the robustness of the features can be improved in these regions. This section extends LBP to 3-valued codes, Local Ternary Patterns (LTP), in which gray-levels in a zone of width ±*t* around *ic* are quantized to zero, ones above this are quantized to +1 and ones below it to -1, *i.e*. the indicator *s*(*u*) is replaced with a 3-valued function:

$$s'(u, i_c, t) = \begin{cases} 1, & u \geq i_c + t \\ 0, & |u - i_c| < t \\ -1, & u \leq i_c - t \end{cases}$$

and the binary LBP code is replaced by a ternary LTP code. Here *t* is a user-specified threshold – so LTP codes are more resistant to noise, but no longer strictly invariant to gray-level transformations. The LTP encoding procedure is illustrated in Fig. 3. Here the threshold *t* was set to 5, so the tolerance interval is [49*;* 59].

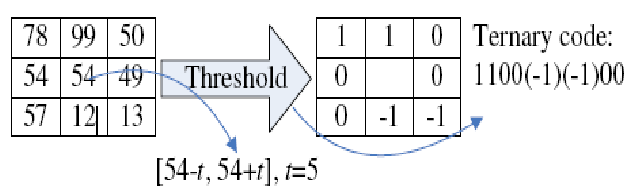


Fig3: Illustration of the basic LTP operator.

When using LTP for visual matching we could use 3^n valued codes, but the uniform pattern argument also applies in the ternary case. For simplicity, the experiments below use a coding scheme that splits each ternary pattern into its positive and negative halves as illustrated in Fig. 4, subsequently treating these as two separate channels of LBP descriptors for which separate histograms and similarity metrics are computed, combining the results only at the end of the computation. LTP's bear some similarity to the texture spectrum (TS) technique from the early 1990's . However TS did not include preprocessing, thresholding, local histograms or uniform pattern based dimensionality reduction and it was not tested on faces.

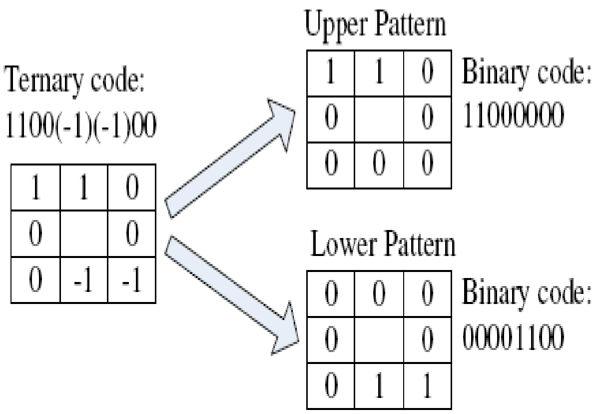


Fig4: Splitting an LTP code into positive and negative LBP codes.

3.3 Distance Transform based Similarity Metric

Ahonen introduced an LBP based method for face recognition that divides the face into a regular grid of cells and histograms the uniform LBP's within each cell, finally using nearest neighbor classification in the X^2 histogram distance for recognition

$$\chi^2(p,q) = \sum_i \frac{(p_i - q_i)^2}{p_i + q_i}$$

Here *p, q* are image region descriptors (histogram vectors), respectively. This method gave excellent results on the FERET dataset. However subdividing the face into a regular grid seems somewhat arbitrary: the cells are not necessarily well aligned with facial features, and the partitioning is likely to cause both aliasing (due to abrupt spatial quantization of descriptor contributions) and loss of spatial resolution (as position within each grid cell is not coded). Given that the overall goal of coding is to provide illumination- and outlier-robust visual correspondence with some leeway for small spatial deviations due to misalignment, it seems more appropriate to use a Hausdorff-distance-like similarity metric that takes each LBP or LTP pixel code in image *X* and tests whether a similar code appears at a nearby position in image *Y,* with a weighting that decreases smoothly with image distance. Such a scheme should be able to achieve discriminant appearance based image matching with a well-controllable degree of spatial looseness. We can achieve this using Distance Transforms. Given a 2-D reference image *X*, we find its image of LBP or LTP codes and transform this into a set of sparse binary images b^k, one for each possible LBP or LTP code value *k* (*i.e*. 59 images for uniform codes). Each b^k specifies the pixel positions at which its particular LBP or LTP code value appears. We then calculate the distance transform image d^k of each b^k. Each pixel of d^k gives the distance to the nearest image *X* pixel with code *k* (2D Euclidean distance is used in the experiments below). The distance or similarity metric from image *X* to image *Y* is then:

$$D(X,Y) = \sum_{\text{pixels } (i,j) \text{ of } Y} w(d_X^{k_Y(i,j)}(i,j))$$

Here, *kY* (i, *j*) is the code value of pixel (*i, j*) of image *Y* and

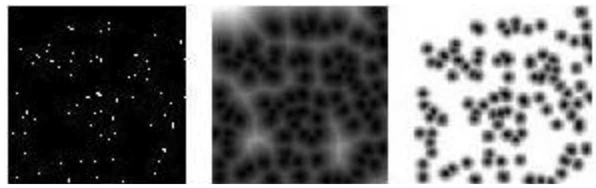


Fig5: From left to right: a binary layer, its distance transform, and the truncated linear version of this.

w () is a user-defined function giving the penalty to include for a pixel at the given spatial distance from the nearest matching code in *X*. In our experiments we tested both Gaussian similarity metrics $w(d) = \exp\{-(d/\sigma)^2/2\}$ and truncated linear distances $w(d) = \min(d,\tau)$. Their performance is similar, with truncated distances giving slightly better results overall. For 120×120 face images in which an iris or nostril has a radius of about 6 pixels and overall global face alignment is within a few pixels, our default parameter values were σ = 3 pixels and τ = 6 pixels. Fig. 5 shows an example of a binary layer and its distance transforms. For a given target the transform can be computed and mapped through *w*() in a preprocessing step, after which matching to any subsequent image takes *O* (number of pixels) irrespective of the number of code values.

4. EXPERIMENTS

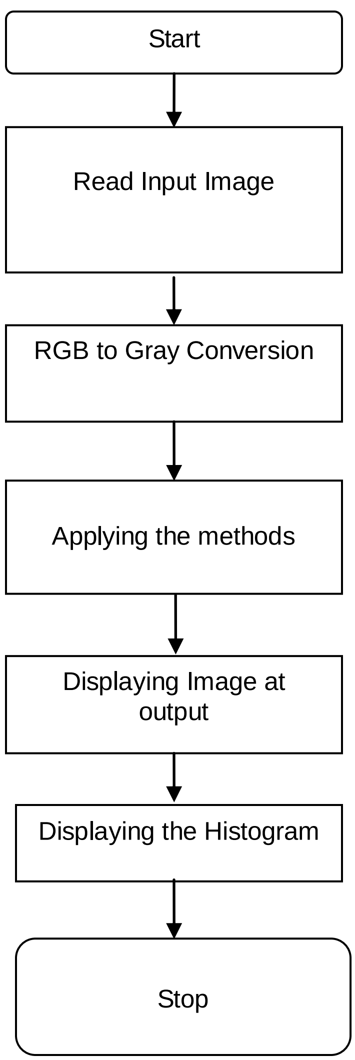
We illustrate the effectiveness of our methods by presenting experiments on three large-scale face data sets with difficult lighting conditions: Extended Yale B, CAS-PEAL-R1, and Face Recognition Grand Challenge version 2 Experiment 4. For each data set we use its standard evaluation protocol in order to facilitate comparison with previous work. We divide the results into two sections, the first focusing on nearest neighbour classification with various LBP/LTP based feature sets and distance metrics, and the second on KLDA based classifiers with combinations of LBP and Gabor features. Note that unlike subspace based classifiers such as KLDA, the Nearest Neighbour methods do not use a separate training set – they simply compare probe images directly to gallery ones using a given (not learned) feature set and distance metric. They are thus simpler, but in general less discriminant than methods that learn subspaces, feature sets or distance metrics. In both cases we compare several different preprocessing methods. The benefits of preprocessing are particularly marked for Nearest

Neighbour classifiers. We only show results for LBP/LTP here, but additional experiments showed that our preprocessing method substantially increases the performance of Nearest Neighbour classifiers for a wide variety of other image descriptors including pixel or Gabor based linear or Kernelized Eigen or Fisher-faces under a range of descriptor normalizations and distance metrics.

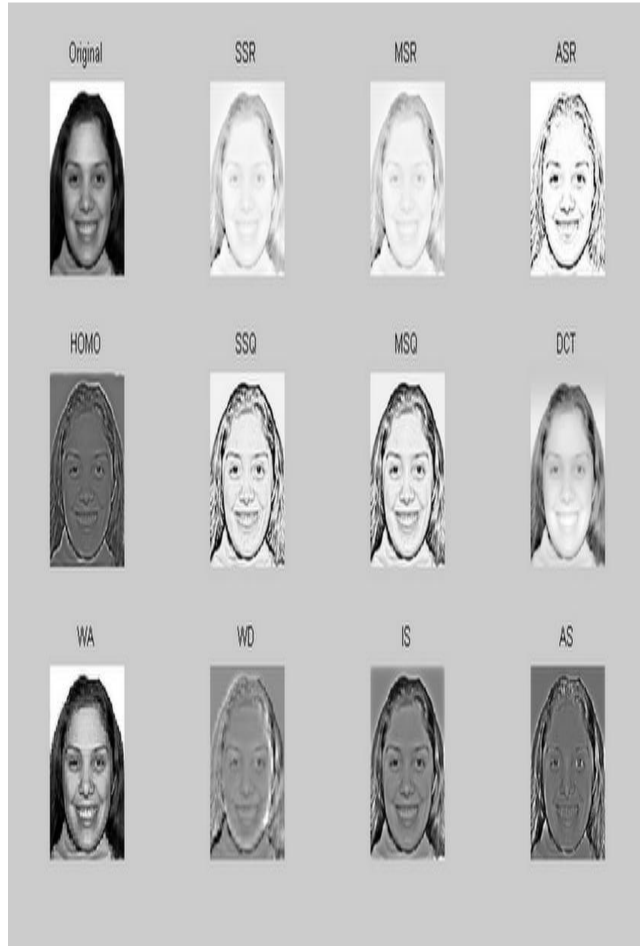
5. ALGORITHM

- **Paging the input image**
- **Preprocessing the image to remove noise**
- **Extracting the features using filters**
- **Normalizing the levels of Contrast**
- **Displaying the output**

5.1FLOW CHART



6. RESULTS



These are the different output images for a given input image under different lighting conditions.So that we can easily recognize under any conditions.

7.CONCLUSION

We have presented new methods for face recognition under uncontrolled lighting based on robust preprocessing and an extension of the Local Binary Pattern (LBP) local texture descriptor. There are following main contributions: (*i*) a simple, efficient image preprocessing chain whose practical recognition performance is comparable to or better than current (often much more complex) illumination normalization methods; (*ii*) a rich descriptor for local texture called Local Ternary Patterns (LTP) that generalizes LBP while fragmenting less under noise in uniform regions: (*iii*) a distance transform based similarity metric that captures the local structure and geometric variations of LBP/LTP face images better than the simple grids of histograms that are currently used; and (*iv*) a heterogeneous feature fusion-based recognition framework that combines two popular feature sets – Gabor wavelets and LBP – with robust illumination normalization and a kernelized discriminative feature extraction method. The combination of these enhancements gives the state of the art performance on three well-known large-scale face datasets that contain widely varying lighting conditions.

8. REFERENCES

1. S. Shan, W. Gao, B. Cao, and D. Zhao, "Illumination normalization for robust face recognition against varying lighting conditions," in Proc.AMFG, Washington, DC, 2003, p. 157.

2. Y. Adini, Y. Moses, and S. Ullman, "Face recognition: The problem of compensating for changes in illumination direction," IEEE Trans.
Pattern Anal. Mach. Intell., vol. 19, no. 7, pp. 721–732, Jul. 1997.

3. T. Ahonen, A. Hadid, and M. Pietikainen, "Face recognition with local binary patterns," in Eur. Conf. Comput. Vis., Prague, Czech Republic,
2005, pp. 469–481.

4. R. Gross and V. Brajovic, "An image preprocessing algorithm for illumination invariant face recognition," in *Proc. AVBPA*, 2003, pp. 10–18.

5. G.Borgefors, "Distance transformations in digital images,"Comput.Vis., Graphics Image Process., vol. 34, no. 3, pp. 344–371, 1986.

6. R. Brunelli and T. Poggio, "Face recognition: Features versus Templates,"IEEE Trans. Pattern Anal. Mach. Intell., vol. 15, no. 10, pp.1042–1052, Oct. 1993.