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AN EXTENSION OF THE LBP LOCAL TEXTURE FEATURE SETS FOR FACE RECOGNITION UNDER UNCONTROLLED LIGHTNING BASED ON ROBUST PRE PROCESSING

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Abstract— **The most important challenge for practical face recognition systems is making recognition more reliable under uncontrolled lighting conditions. We handle this by combining the strengths of robust illumination normalization, local texture-based face representations, kernel based feature extraction, distance transform based matching and multiple feature fusion. Specifically, we make three main contributions: 1) 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; 2) we introduce local ternary patterns (LTP), a generalization of the local binary pattern (LBP) local texture descriptor that is more discriminate 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 3) we further improve robustness by adding Kernel principal component analysis (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, and visual features.

I. INTRODUCTION

Over the past several decades **face recognition** has received a great deal of attention from the scientific and industrial communities owing to its wide range of applications in information security and access control, law enforcement, surveillance, and more generally image understanding. Most of the traditional methods were initially developed with face images collected under relatively well-controlled conditions and in practice they have difficulty in dealing with the range of appearance variations that commonly occur in unconstrained natural images due to illumination, pose, facial expression, aging, partial occlusions, etc.

This paper focuses mainly on the issue of robustness to lighting variations. Traditional approaches for dealing with this issue can be broadly classified into three categories: 1.appearance-based, 2.normalization-based and 3.feature-based methods. In direct appearance-based approaches, training examples are collected under different lighting conditions and directly (i.e., without undergoing any lighting preprocessing) used to learn a global model of the possible illumination variations. However this method requires a large number of training images and an expressive feature set.

Normalization based approaches seek to reduce the image to a more “canonical” form in which the illumination variations are suppressed. Histogram equalization is one simple example, but purpose-designed methods often exploit the fact that (on the scale of a face) naturally occurring incoming illumination distributions typically have predominantly low spatial frequencies and soft edges so that high-frequency information in the image is predominantly signal (i.e., intrinsic facial appearance).

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The third approach extracts illumination-insensitive feature sets [2], [3], [5], [13] directly from the given image. These feature sets range from geometrical features to image derivative features such as edge maps [13], local binary patterns (LBP) [2], [3], Gabor wavelets [1], and local autocorrelation filters [5].

In this paper we propose an integrative framework that combines the strengths of all three of the above approaches. The overall process can be viewed as a pipeline consisting of image normalization, feature extraction, and subspace representation, as shown in the following figure.

Fig. 1 full face recognition method.

Each stage increases resistance to illumination variations and makes the information needed for recognition more manifest. We will investigate several aspects of this frame work.

1. The relationship between image normalization and feature sets.

2. Robust feature sets and feature comparison strategies.

3. Fusion of multiple feature sets.

II. ILLUMINATION NORMALIZATION

This is a preprocessing chain run before feature extraction that incorporates a series of stages designed to counter the effects of illumination variations, local shadowing and highlights while preserving the essential elements of visual appearance. Fig.2 illustrates the three main stages and their effect on a typical face image.

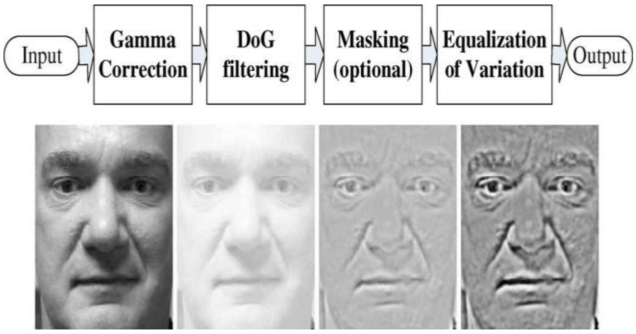

Fig. 2.stages of our image preprocessing pipeline

1. **Gamma Correction** is a nonlinear gray-level transformation that replaces gray-level I with I^γ (for γ> 0) or log (I) (for γ = 0), where γ ϵ [0; 1] is a user-defined parameter. This enhances the local dynamic range of the image in dark or shadowed regions while compressing it in bright regions and at highlights.

2. **DoG filtering** is a convenient way to achieve the resulting band pass behavior. Fine details remain critically important for recognition so the inner (smaller) Gaussian is typically quite narrow (σ0 ≤ 1 pixel), while the outer one might have σ1 of 2–4 pixels or more, depending on the spatial frequency at which low frequency information becomes misleading rather than informative.

3. Masking. If facial regions (hair style, beard . . .) that are felt to be irrelevant or too variable need to be masked out, the mask should be applied at this point. Otherwise, either strong artificial gray-level edges are introduced into the DoG convolution, or invisible regions are taken into account during contrast equalization.

4. Contrast Equalization. The final stage of our preprocessing chain rescales the image intensities to standardize a robust measure of overall contrast or intensity variation. It is important to use a robust estimator because the signal typically contains extreme values produced by highlights, small dark regions such as nostrils, garbage at the image borders, etc.

III. LOCAL TERNARY PATTERNS

A. Local Binary Patterns (LBP)

T.Ojala et al. [12] introduced Local Binary Patterns (LBPs) as a means of summarizing local gray-level structure. The LBP operator takes a local neighborhood around each pixel, thresholds the pixels of

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the neighborhood at the value of the central pixel and uses the resulting binary-valued image patch as a local image descriptor.

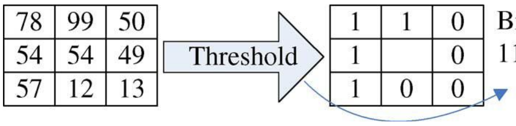

Fig.3. Illustration of the basic LBP operator.

It was originally defined for 3× 3 neighborhoods, giving 8-bit integer LBP codes based on the eight pixels around the central one. Formally, the LBP operator takes the form

$$\mathrm{LBP}(x_c, y_c) = \sum_{n=0}^{7} 2^n s(i_n - i_c) \qquad (1)$$

where in this case 'n' runs over the 8 neighbors of the central pixel *c*, *ic*, *in*, and 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. 3.

B. Local Ternary Patterns (LTP)

LBPs have proven to be highly discriminative features for texture classification [12] 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.

This section extends LBP to 3-valued codes, 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

$$s^1(u, i_c, t) = \begin{cases} 1 & u \geq i_c + t \\ 0 & u - i_c < t \\ -1 & u \leq i_c - t \end{cases} \qquad (2)$$

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. The LTP encoding procedure is illustrated in Fig. 4. Here the threshold't' was set to 5, so the tolerance interval is [49, 59].

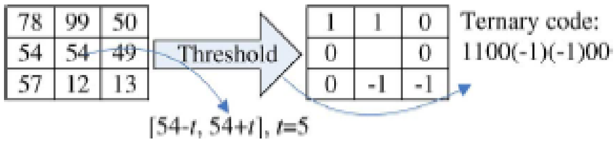

Fig. 4. Illustration of the basic LTP operator

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. 5, 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.

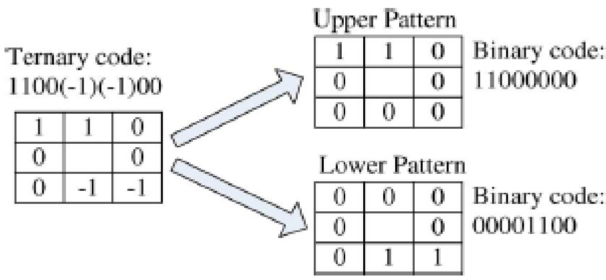

Fig. 5. Splitting LTP code into positive and negative LBP codes.

IV. ILLUMINATION-INSENSITIVE FACE-RECOGNITION (A FRAME WORK)

This section details our robust face recognition framework (cf. Fig. 2). The full method incorporates the aforementioned preprocessing chain and LBP or LTP features with distance transform based comparison.

The selection of an expressive and complementary set of features is crucial for good performance. Our initial experiments suggested that two of the most successful local appearance descriptors, Gabor wavelets and LBP (or its extension LTP), were promising candidates for fusion. LBP is good at coding fine details of facial appearance and texture, whereas Gabor features encode facial shape and appearance over a range of coarser scales. Both representations are rich in information and computationally efficient, and their complementary nature makes them good candidates for fusion.

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In face recognition, Kernel Linear Discriminant Analysis (KLDA [11]) has proven to be an effective method of extracting discriminant information from a high-dimensional kernel feature space under subspace constraints such as those engendered by lighting variations [10].we use Gaussian kernels $k(p,q) = e^{dist\,(p,q)/(2\sigma^2)}$, where $dist(p,q) = ||p-q||^2$ is for Gabor wavelets and χ^2 histogram distance (3) for LBP feature sets.

$$\chi^2(p,q) = \sum_i \frac{(p_i - q_i)^2}{p_i + q_i} \qquad (3)$$

We now summarize our modified KLDA method. Let $\phi()$ be the mapping to the implicit feature space, $\Phi = [\phi(x_1), \dots, \phi(x_m)]$ be the operator mapping the m training examples to the feature space, and $\bar{\Phi} = \boldsymbol{\Phi\pi} = [\dots, \boldsymbol{\phi}(\boldsymbol{x_i}) - \boldsymbol{\mu} \dots]$ be the operator of centered training examples, where $\pi = I - (1/m)1_m 1_m^T$ and $\mu = (1/m)\boldsymbol{\Phi 1_m}$. To perform LDA, we need explicit orthogonal coordinates for this implicit feature space. If we had $\bar{\Phi}$ in explicit form we could find its thin SVD WDU^T and project to coordinates using $W^T = (\bar{\Phi} U D^{-1})^T$. We cannot do this directly, but we can find U and D=$\Lambda^{1/2}$ from the thin eigendecomposition of the centred kernel matrix of the training examples $\bar{K} = \pi K \pi = \pi \Phi^T \Phi \pi = U \Lambda U^T$. This allows the projection of any example x to be calculated using $\Lambda^{1/2} U^T \pi k_x$ where $k_x = \Phi^T \phi(x)$ is the kernel vector of x against the training examples. Using these coordinates, we find the projected within-class and between-class scatter matrices S_W, S_B, from which a basis V for the kernel discriminative subspace is obtained by solving the thin LDA eigen decomposition $(S_W + \in I)^{-1} S_B V = VE$ for eigenvectors V and eigenvalues E. Here, ∈ is a small regularization constant (10^{-3} below) and I is the identity matrix. The optimal projection operator is then $P = \bar{\Phi} U \Lambda^{-1/2} V$ and test examples x can be projected into the optimal discriminant space by

$$\boldsymbol{\Omega_x} = \boldsymbol{P^T \phi(x)} = \boldsymbol{V^T} \Lambda^{-1/2} \boldsymbol{U^T k_x} \qquad (4)$$

The projected feature vectors Ω_{test} are classified using the nearest neighbor rule and the cosine "distance"

$$\boldsymbol{d_{cos}(\Omega_{test}, \Omega_{template})} = \frac{\boldsymbol{\Omega_{test}^T \Omega_{template}}}{\boldsymbol{||\Omega_{test}|| \, ||\Omega_{template}||}} \qquad (5)$$

Where $\boldsymbol{\Omega_{template}}$ is a face template in the gallery set. Other similarity metrics such as L_1,L_2, or Mahalanobis distances could be used, but [10] found that the cosine distance performed best among the metrics it tested on this database, and our initial experiments confirmed this.

When a face image is presented to the system, its Gabor wavelet and LBP features are extracted, separately projected into their optimal discriminant spaces (4) and used to compute the corresponding distance scores (5). Each score is normalized using the "*z-score*" method [7]

$$\boldsymbol{z = \frac{s - \mu}{\sigma}} \qquad (6)$$

where μ, σ are, respectively, the mean and standard deviation of s over the training set.

Finally, the two scores z_{galbor} and z_{LBP} are fused at the decision level. Notwithstanding suggestions that it is more effective to fuse modalities at an earlier stage of processing [7], our earlier work found that although feature-level and decision-level fusion both work well, decision-level fusion is better in this application. Thus, we fuse the Gabor and LBP similarity scores using the simple sum rule: z_{Galbor} + z_{LBP}. The resulting similarity score is input to a simple Nearest Neighbor (NN) classifier to make the final decision.

Fig. 6 gives the overall flowchart of the proposed method. We emphasize that it includes a number of elements that improve recognition in the face of complex lighting variations.

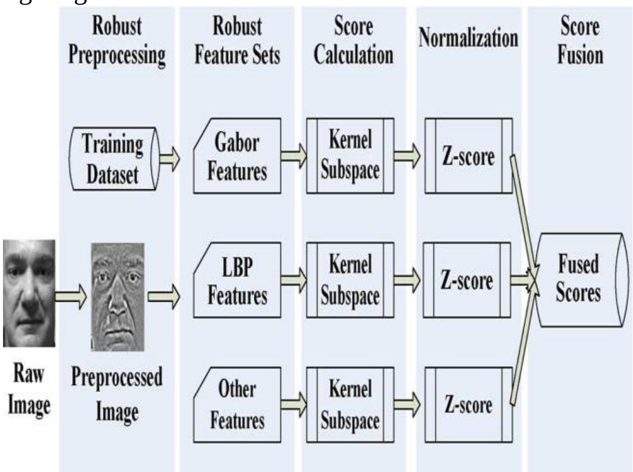

Fig. 6 Architecture of our multi-feature subspace based face recognition method.

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1) we use a combination of complementary visual features—LBP and Gabor wavelets; 2) preprocessing—which is usually ignored in previous work on these feature sets [2], [3] greatly improves robustness; 3) the inclusion of kernel subspace discriminants increases discriminatively while compensating for any residual variations.

V. RESULTS & DISCUSSION

Figs.7&8. shows the extent to which nearest neighbor based LBP face recognition can be improved by combining three of the enhancements proposed here: 1.preprocessing (PP); 2.replacing LBP with LTP; and 3.replacing local histogramming and the X^2 histogram distance with the Distance Transform based similarity metric (DT). After all feature extractions, it is then recognized from the database, which all the steps we done before will be exected at background and compare the features and displays the recognized output from the database.

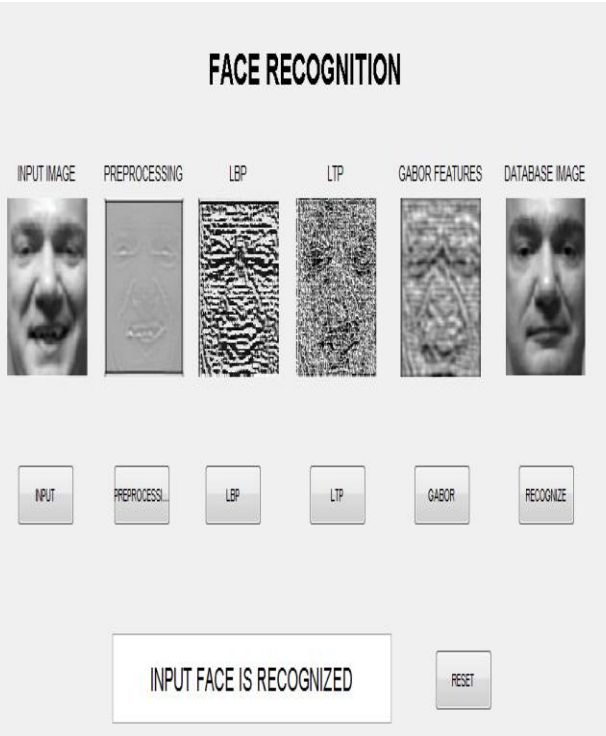

Fig.7. ***Final output which the query image has been detected from database image***

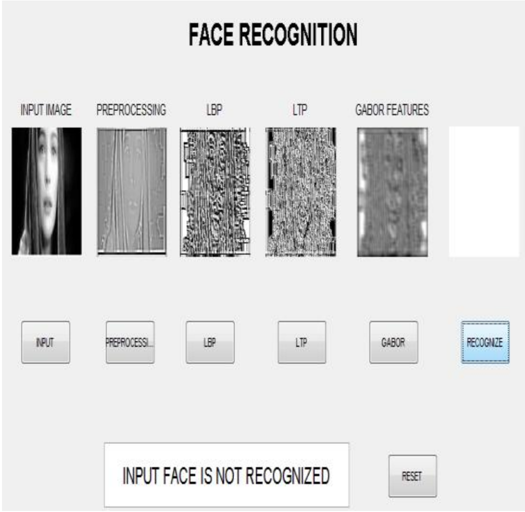

Fig.8. The output image which query image is not with database

IV CONCLUSION

We have presented new methods for face recognition based on robust preprocessing under uncontrolled lighting conditions. The main contributions are as follows: 1) an efficient image preprocessing chain whose practical recognition performance is comparable to or better than current methods. 2) a rich descriptor for local texture called LTP that generalizes LBP. 3) 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 4) a fusion-based recognition framework that combines two popular feature sets—Gabor wavelets and LBP.

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