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An Effective Face Recognition in Various Lighting Conditions Using LBP/LTP Techniques

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***Abstract* - Making recognition is more reliable under uncontrolled lighting conditions is one of the most important challenges for practical face recognition systems. We tackle this by combining following methods. The first step is simple and efficient preprocessing chain. The preprocessing is used to avoid the unwanted illumination effects such as Non-uniform illumination, Shadowing & highlights, aliasing, blurring and noise. Second step includes local binary pattern (LBP) and local ternary pattern methods (LTP). LBP is possible to describe the texture and shape of a digital image .LTP is a generalization of the local binary pattern (LBP). Local texture descriptor that is more discriminant and less sensitive to noise in uniform regions. The final step is used to improve robustness by adding 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, preprocessing, kernel principal components analysis, local patterns, visual features**

I. Introduction

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..Numerous approaches have been proposed, including eigenfaces, fisherfaces, laplacianfaces, nearest feature line-based subspace analysis, neural networks, elastic bunch graph matching wavelets and kernel methods. Most of these 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: appearance-based, normalization-based, and 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, Direct learning of this kind makes few assumptions but it requires a large number of training images. Normalization based approaches seek to reduce the image to a more "canonical" form in which the illumination variations are suppressed. The third approach extracts illumination-insensitive feature directly from the given image. These feature sets range from geometrical features to image derivative features such as edge maps, local binary patterns, Gabor wavelets and local autocorrelation filters. Although such features offer a great improvement on raw gray values, their resistance to the complex illumination variations that occur in real-world face images is still quite limited.

A. Stages of Full Face Recognition Method

The overall process can be viewed as a pipeline consisting of image normalization, feature extraction, and subspace representation. Each stage increases resistance to illumination variations and makes the information needed for recognition more manifest.

Fig.1 Stages of full face recognition method

Normalization is known to improve the performance of simple subspace methods [e.g., principal component analysis (PCA)] or classifiers (e.g., nearest neighbors) based on image pixel representations. Robust feature sets gives good performance under illumination variations but there is still room for improvement. For example, LBP 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 (LTPs) that is more discriminant and less sensitive to noise in uniform regions. Combining two of the most successful local face representations, Gabor wavelets and LBPs, 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.

B. Illumination Normalization

1) Pre Processing:

This section describes our illumination normalization method. 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.

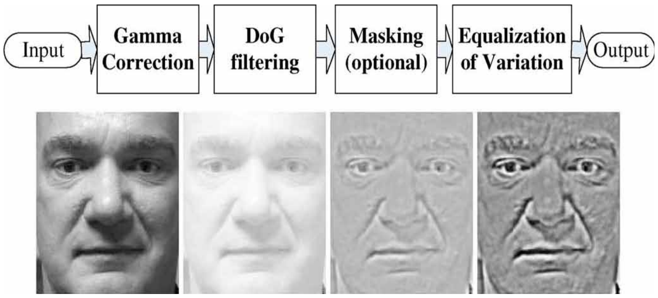


Fig.2 Preprocessing

2) Gamma Correction

This is a nonlinear gray-level transformation that replaces gray level I with I (for γ > 0) or log(I) (for γ = 0), where γ = [0; 1] is a user-defined parameter. It has the effect of enhancing the local dynamic range of the image in dark or shadowed regions, while compressing it in bright regions and at highlights. The basic principle is that the intensity of the light reflected from an object is the product of the incoming illumination L (which is piecewise smooth for the most part) and the local surface reflectance R (which carries detailed object-level appearance information). We want to recover object-level information independent of illumination, and taking logs makes the task easier by converting the product into a sum: for constant local illumination, a given reflectance step produces a given step in log(I) irrespective of the actual intensity of the illumination. In practice a full log transformation is often too strong, tending to over-amplify the noise in dark regions of the image, but a power law with exponent in the range [0; 0:5] is a good compromise. Here we use γ= 0.2 as the default setting.

3) Difference of Gaussian Filtering

Gamma correction does not remove the influence of overall intensity gradients such as shading effects. Shading induced by surface structure is potentially a useful visual cue but it is predominantly low frequency spatial information that is hard to separate from effects caused by illumination gradients. High pass filtering removes both the useful and the incidental information, thus simplifying the recognition problem and in many cases increasing the overall system performance. Similarly, suppressing the highest spatial frequencies reduces aliasing and noise, and in practice it often manages to do so without destroying too much of the underlying signal on which recognition needs to be based. DOG filtering is a convenient way to obtain the resulting bandpass behaviour. Fine spatial detail is critically important for recognition so the inner (smaller) Gaussian is typically quite narrow (σ0 1 pixel), while the outer one might have of σ1 2–4 pixels or more, depending on the spatial frequency at which low frequency information becomes misleading rather than informative. Given the strong lighting variations in our datasets we find that σ1 ~2 typically gives the best results, but values up to about 4 are not too damaging and may be preferable for datasets with less extreme lighting variations. LBP and LTP seem to benefit from a little smoothing, perhaps because pixel based voting is sensitive to aliasing artifacts. Below we use σ0 = 1:0 and σ1= 2:0 by default3. We implement the filters using explicit convolution. If the face is part of a larger image the gamma correction and prefilter should be run on an appropriate region of this before cutting out the face image. Otherwise extend-as-constant boundary conditions should be used: using extend-as-zero or wrap-around (FFT) boundary conditions significantly reduces the overall performance, in part because it introduces strong gradients at the image borders that disturb the subsequent contrast equalization stage. If DOG is run without prior gamma normalization, the resulting images clearly show the extent to which local contrast (and hence visual detail) is reduced in shadowed regions.

4) Masking

If a mask is needed to suppress facial regions that are felt to be irrelevant or too variable, it should be applied at this point. Otherwise, either strong artificial gray-level edges are introduced into the convolution, or invisible regions are taken into account during contrast equalization.

5) Contrast Equalization

The final step of our preprocessing chain globally 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 still contains a small admixture of extreme values produced by highlights, garbage at the image borders and small dark regions such as nostrils.

II. Robust Feature Extraction

A. Local Binary Patterns

There exist several methods for extracting the most useful features from (preprocessed) face images to perform face recognition. One of these feature extraction methods is the Local Binary Pattern (LBP) method. With LBP it is possible to describe the texture and shape of a digital image. This is done by dividing an image into several small regions from which the features are extracted. These features consist of binary patterns that describe the surroundings of pixels in the regions. The obtained features from the regions are concatenated into a single feature histogram, which forms a representation of the image. Images can then be compared by measuring the similarity (distance) between their histograms. According to several studies, face recognition using the LBP method provides very good results, both in terms of speed and discrimination performance. Because of the way the texture and shape of images is described, the method seems to be quite robust against face images with different facial expressions, different lightening conditions, image rotation and aging of persons. The local binary operator works with the eight neighbors of a pixel, using the value of this center pixel as a threshold. If a neighbor pixel has a higher gray value than the center pixel (or the same gray value) than a one is assigned to that pixel,else it gets a zero. The LBP code for the center pixel is then produced by concatenating the eight ones or zeros to a binary code

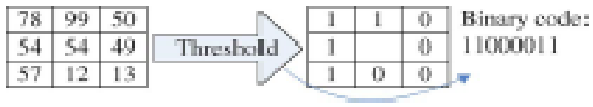


Fig.3 Basic LBP operator

The LBP-method can be applied on images (of faces) to extract features which can be used to get a measure for the similarity between these images. The main idea is that for every pixel of an image the LBP-code is calculated. The occurrence of each possible pattern in the image is kept up. The histogram of these patterns, also called labels, forms a feature vector, and is thus a representation for the texture of the image. These histograms can then be used to measure the similarity between the images, by calculating the distance between the histograms.

B. Local Ternary Patterns

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.

LBP's are resistant to lighting effects in the sense that they are invariant to monotonic gray-level transformations, and they have been shown to have high discriminative power for texture classification. However because they threshold at exactly the value of the central pixel they tend to be sensitive to noise, especially in near-uniform image regions. Given that many facial regions are relatively uniform, it is potentially useful to improve the robustness of the underlying descriptors in these areas. This section extends LBP to 3-valued codes, Local Ternary Patterns, in which gray levels in a zone of width +-t around i are quantized to zero, ones above this are quantized to +1 and ones below it to -1, and the binary LBP code is replaced by a ternary LTP code. Here t is a user-specified threshold (so LTP codes more resistant to noise, but no longer strictly invariant to gray level transformations).

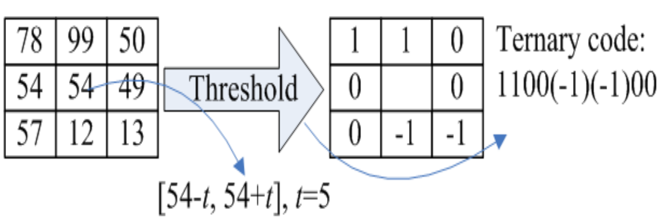


Fig.4 Basic LTP operator

When using LTP for visual matching we could use 3n 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 parts as illustrated in fig. subsequently treating these as two separate channels of LBP descriptors for which separate histograms and similarity metrics are computed, combining these only at the end of the computation. LTP's bear some similarity to the texture spectrum (TS). However TS did not include preprocessing, thresholding, local histograms or uniform pattern based dimensionality reduction and it was not tested on faces.

C. A Framework For Illumination-Insensitive Face Recognition

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. In face recognition, it is widely accepted that discriminant based approaches offer high potential performance and improved robustness to perturbations such as lighting variations and that kernel methods provide a well-founded means of incorporating domain knowledge in the discriminant.In particular, Kernel Linear Discriminant Analysis (KLDA) 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.

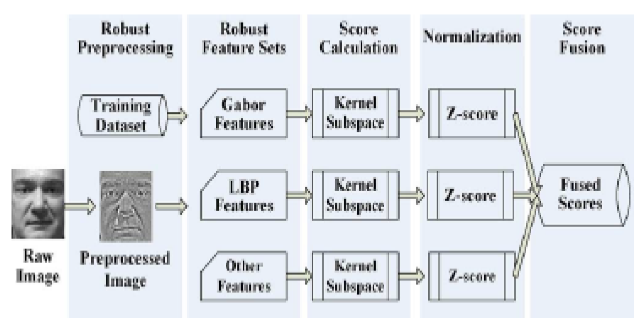


Fig.5 Overall architecture of our multi-feature subspace based face recognition method

Fig.5 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:we use a combination of complementary visual features—LBP and Gabor wavelets; 2) the features are individually both robustand information-rich; 3)preprocessing—which is usually ignored in previous work on these feature sets greatly improves robustness; 4) the inclusion of kernel subspace discriminants increases discriminativity while compensating for any residual variations. As we will show below,each of these factors contributes to the overall system performance

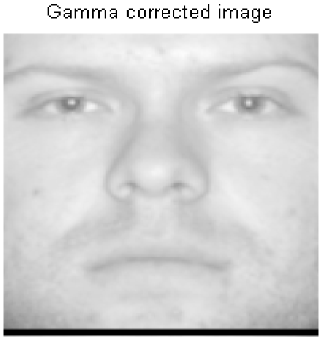
III. Results

Face recognition can be improved by combining three of the enhancements proposed here: using preprocessing, replacing LBP with LTP and replacing local histogramming and the histogram distance with the distance transform-based similarity metric (DT).The absolute recognition rate is increased by about 23.5% relative to standard un preprocessed LBP .Preprocessing alone boosts the performance by 20.2% (from 75.5%95.7%). Replacing LBP with LTP improves the recognition rate.

Input face image

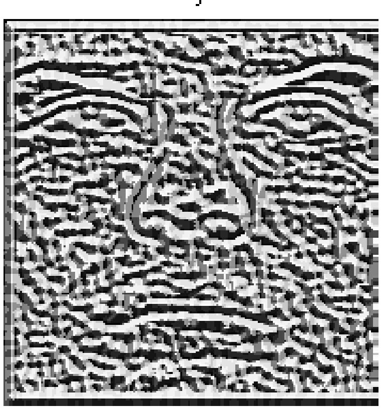
Difference of gaussian filtered image

Gamma corrected image



Contrast Equalization

Local Binary Patterns



IV. Conclusion

These methods of face recognition under uncontrolled lighting based on robust preprocessing and an extension of the LBP local texture descriptor. The main contributions are as follows: 1) a simple, efficient image preprocessing chain whose practical recognition performance is comparable to or better than current illumination normalization methods; 2) a rich descriptor for local texture called LTP that generalizes LBP while fragmenting less under noise in uniform regions: 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 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 analysis method. This provides new insights into the role of robust preprocessing methods played in dealing with difficult lighting conditions and thus being useful in the designation of new methods for robust face recognition.

In future, apply the kernelized principal component analysis in the same data base for face recognition.

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