INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH & DEVELOPMENT

ISSN: 2278 – 0211 (Online)

Face Recognition Underuncontrolled Conditions Based On Partial Least Squares

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Abstract:

The goal of matching unknown faces against a gallery of known people, the face identification is necessary. There are very accurate techniques to perform face identification in controlled environments. but face identification under uncontrolled environments is still an problem. face recognition which considers both shape and texture information to represent face images.The face area is first divided into small regions from which Local Binary Pattern (LBP) histograms are extracted and concatenated into a single, spatially enhanced feature histogram efficiently representing the face image. A large and rich set of feature descriptor for face identification using partial least squares to perform uncontrolled conditions .The method is evaluated on Facial Recognition Technology (FERET) and Face Recognition Grand Challenge (FRGC) data sets .This Algorithms is performed under uncontrolled conditions such as uncontrolled lighting and changes in facial expressions, recognition rates increases Partial Least Squares (PLS) analysis, an efficient dimensionality reduction technique, one which preserves significant discriminative information, to project the data onto a much lower dimensional subspace (20 dimensions reduced from the original 170,000).

Key words : *Face identification, feature combination, feature selection, LBP, partial least squares (PLS)*

1.Introduction

FACE recognition has become a very active research area in recent years, mainly driven by its broad applications suchas in public security, human–computer interaction, and financial security. The two primary face recognition tasks are identification and verification. In the identification task, an image of an unknown person is matched to a gallery of known people. In verification, the task is to accept or deny the identity claimed bya person. Therefore, given two face images, the goal is to decide whether the two images are of the same individual or not. face recognition underwell-controlled acquisition conditions is relatively mature and provides high recognition rates even when a large number of subjects is in the gallery this task is performed under uncontrolled conditions such as uncontrolled lighting and changes in facial expressions, recognition rates significantly decrease. Face appearances may change when acquisition conditions are uncontrolled, making the recognition problem harder.

The availability of numerous commercial face recognition systems [1] attests to the significant progress achieved in the research field [2]. Therefore, the goal of the ongoing research is to increase the robustness of the systems against different factors. Ideally, we aim to develop a face recognition system which mimics the remarkable capabilities of human visual perception. Before attempting to reach such a goal, one needs to continuously learn the strengths and weaknesses of the proposed techniques in order to determine new directions for future improvements.

To facilitate this task, the FERET database and evaluation methodology have been created [3]. The main goal of FERET is to compare different face recognition algorithms on a common and large database and evaluate their performance against different factors such as facial expression, illumination changes, aging (time between the acquisition date of the training image and the image presented to the algorithm) etc.

2.Methodology

In our proposed systemface recognition which considers both shape and texture information to represent the face images. The face image is first divided into small regions from which the Local Binary Pattern (LBP) features are extracted and combining an increasing number of feature descriptors weighted by partial least squares concatenated into a single feature histogram efficiently representing the face image .The textures of the facial regions are locally encoded by the LBP patterns while the whole shape of the face is recovered by the construction of the face feature histogram. The idea behind using the LBP features is that the face images can be seen as composition of micro-patterns which are invariant with respect to monotonic grey scale transformations. Combining these micro-patterns, a global description of the face image is obtained.

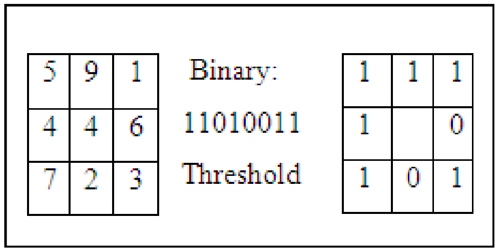

Figure 1: The basic LBP operator

This textures of the facial regions are locally encoded by the LBP patterns. this give shape of the face feature . LBPfeatures is that the face images can be seen as composition of micro-patterns which are invariant with respect to monotonic grey scale transformations.

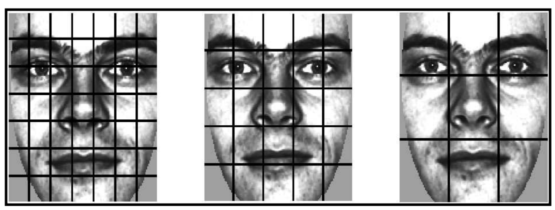

Figure 2: A facial image divided into 3rectangular

2.1.Feature Extraction

2.1.1.<u>Local Binary Pattern</u>

Combining these micro-patterns ,a global description of the face image is obtained.

2.2.Input Image

The Figure 3 shows the input image. The input FACE image is a gray image. It is of default size 576*768. For our convenience, the input FACEimage is resized to 512*512.after cropping and resizing the faces, each sample is decomposed into overlapping blocks ,and then,a set of low level feature descriptors is extracted from eachblocks.

Figure 3: Input Image

The local binary pattern operator works in a 3 × 3 pixel block of an image. The pixels in this block are thresholded by its center pixel value, by powers of two and then summed to obtain a label for the center pixel.As the neighborhood consists of 8 pixels, a total of 28 = 256 different labels can be obtained depending on the relative gray values of the center pixel.LBP characterizes the spatial structure of the local image texture and is invariant to monotonic transformations of the pixel gray values . Its original version labels the pixels of an image by thresholding the 3×3 neighborhood with intensity Gp (p = 0,1,2…..7) with respect to its intensity of the center pixel , then defines

$$S(Gp\text{-}Gc) = \begin{cases} 1 & Gp \geq Gc \\ 0 & Gp < Gc \end{cases}$$

The textures of the facial regions are locally encoded by the LBP patterns while the whole shape of the face is recovered by the construction of the face feature .histogram.

2.3.Different Texture Primitives Detected By The LBP

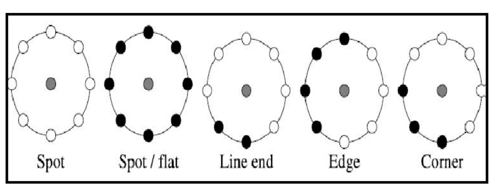

Figure 4: Different texture primitives detected by the LBP

FIG 4.The uniform patterns allows to see the LBP method as a unifying approach to the traditionally divergent statistical and structural models of texture analysis [45]..

2.4.LBP Feature Vector Calculation

- Divide the examined window to cells (e.g. 16x16 pixels for each cell).
- For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.
- Where the center pixel's value is greater than the neighbor, write "1". Otherwise, write "0". This gives an 8-digit binary number (which is usually converted to decimal for convenience).
- Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center).
- Optionally normalize the histogram.
- Concatenate normalized histograms of all cells. This gives the feature vector for the window.

2.5.Construction Of The PLS Regression Model

PLS is a method for modeling relations between sets of observed variables by means of latent variables. The basic idea of PLS is to construct new predictor variables, i.e., latent variables, as linear combinations of the original variables summarized in a matrix of descriptor variables (features) and a vector of response variables. Detailed description of the PLS method can be found in references. Let denote X€R^M an -dimensional feature space, and let y €R be a scalar space representing the response variable. Let the number of samples be . PLS decomposes a mean-centered matrix and a mean-centered vector into

$$X = TP^T$$

$$\mathbf{Y = UQ^T + F}$$

Where T and U are n × p matrices containing extracted latent vectors, the m×p matrix P and the 1×P vector q represent the loadings, and the n×m matrix E and the n×1 vector f are the residuals. Using the nonlinear iterative PLS (NIPALS) algorithm , a set of weight vectors is constructed, stored in matrix $W = (w_1, w_2, \ldots w_{p)}$, such that $[cov(t_i, u_i)]^2$ = max $[cov(X_{wi}, Y)]^2$

where ‖Wi‖ denotes the 2-norm of vector $w_{i,}$ t_i , is the ith column of matrix T,u_i is the ith column of matrix u , and cov ($t_{i,}$ u_i) is the samplecovariance between latent vectors t_i and u_i .

3.Experimentsand Screenshots

3.1.Evaluation On The FERET Data Set

This method is evaluated on standard data set used for face recognition, namely, Facial Recognition Technology (FERET) .The frontal faces in the FERET database are divided into five sets, i.e.,fα (1196 images, used as gallery set containing one image per person), f_b(1195 images, taken with different expressions), f_c (194 images, taken under different lighting conditions), dup1 (722 images, taken at a later date), and dup2 (234 images, taken at least one year apart).

3.2.Results And Comparisons

3.2.1.<u>LBP Image</u>

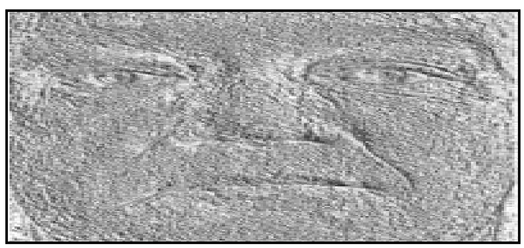

Figure 4: LBP image

FIG 4 shows the LBP image of the input image. it improves the detection performance considerably on FERET datasets. It will be a powerful feature for texture classification.

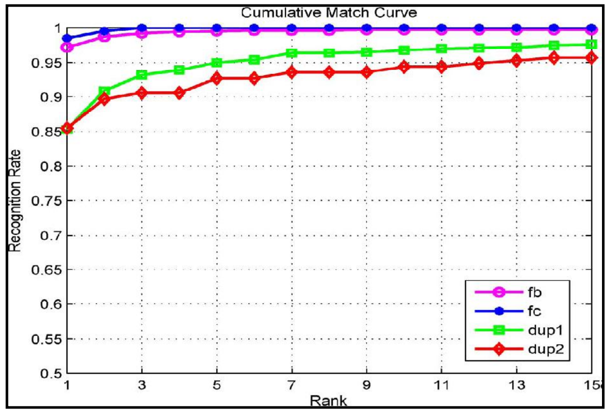

Figure 5: shows the cumulative match curves for FERET data sets

Fig.5. shows the cumulative match curves for all FERET data sets Our method is robust to facial expressions f_b, lightingfc , and aging effect(dul1,dul2) .

METHOD	Fb	Fc	Dup1	Dup2
TAN	92	82	59	52
HGPP	87.3	89	76	70
SIS	89	78	70	65
GRAM-H	90	84.3	68	54
GRAM-L	88	95	78	76
LBP	96	97.2	80.3	82
PLS	97.2	98.5	85.3	85.5

Table 1

Table1 shows the Recognition rates of our algorithms and comparisons with other algorithms for FERET data sets .Recognition rate will high in our algorithm in different uncontrolled conditions.Table I shows the rank-1 recognition rates of previously published algorithms and our algorithm recognition rates on the FERET data set.

3.3.Evaluation On The FRGC Data Set

our method using three experiments from FRGC version 1 that consider 2-D images. Experiment 1 contains a single controlled gallery image and a probe with one controlled still image per subject (183 training images, 152 gallery images, and 608 probe images).

Experiment 2 considers the identification of a person given a gallery with four controlled still images per subject (732 training images, 608 gallery images, and 2 432 probe images). Finally, experiment 4 considers a gallery with one controlled still image per subject and multiple uncontrolled probe images per subject (366 training images, 152 gallery images, and 608 probe images).

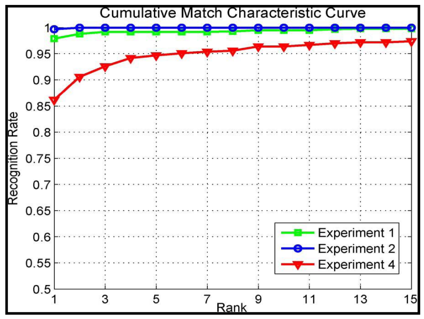

Figure 6: shows the cumulative match curves for FRGC data sets

Fig.6. shows the cumulative match curves for all FRGC data sets . Our method is robust to facial expressions f_b, lightingfc , and aging effect(dul1,dul2) .

Method	Exp.1	Exp.2	Exp.4
PCB[50]	87.6	99.3	-
UMD[26]	94.2	99.3	-
BEE[27]	-	-	37.0
LC1C2[27]	-	-	75.0
TAN[25]	-	-	58.1
HOLAPPA[25]	-	-	63.7
LPQ[28]	-	-	74.5
LIU[29]	-	-	78
ROCA[34]	91.4	-	75.5
LBP	95.5	95.4	80.2
PLS	97.9	99.8	86.2

Table 2

Table II shows the Recognition rates of our algorithms and comparisons with other algorithms for FRGC data sets .Recognition rate will high in our algorithm in different uncontrolled conditions. Table I shows the rank-1 recognition rates of previously published algorithms and our algorithm recognition rates on the FRGC data set.

4.Conclusion & Future Enhancements

Face identification method using a set of low-level feature descriptors analyzed by PLS, which presents the advantages of being both robust and scalable. Experimental results have shown that the method works well for under different conditions. In this method Local Binary Pattern (LBP) histograms are extracted and concatenated into a single, spatially enhanced feature histogram efficiently representing the face image. A large and rich set of feature descriptor for face identification using partial least squares to perform well in uncontrolled conditions. This method is used on Facial Recognition Technology (FERET) and Face Recognition Grand Challenge (FRGC) data sets give highest recognition rates. it increase the speed and no increase in the error rates even larger test sizes compare with cascade rejection classifiers. Finding the performance values, efficiency and sensitivity. Experimental results are reported to demonstrate the performance of the normalization.

5.Reference

1. Face Identification Using Large Feature Sets William Robson Schwartz, Member, IEEE,HuiminGuo, Student Member, IEEE, Jonghyun Choi,Student Member, IEEE, and Larry S. Davis, Fellow, IEEE VOL. 21, NO. 4, APRIL 2012
2. Tan.X and Triggs.B, “Enhanced local texture feature sets for face recognition under difficult lighting conditions,” IEEE Trans.Image Process., vol. 19, no. 6, pp. 1635–1650, Jun. 2010.
3. Schwartz.W.R, Kembhavi.A, Harwood .D, and Davis.L.S, “Human detection using partial least squares analysis,” in Proc. IEEE Int. Conf. Comput. Vis., 2009, pp. 24–31.Ojansivu.V, Rahtu.E, and Heikkilä.J, “Rotation invariant local phase quantization for blur insensitive texture analysis,” in Proc. IEEE Int. Conf. Pattern Recog., 2008, pp. 1–4.
4. Phillips.P.J, Flynn .P.J, Scruggs. Bowyer .W .Chang, K.J Hoffman, Marques .J, Min .J, and Wore .W, “Overview of the face recognition grand challenge,” in Proc. IEEE Conf. Comput. Vis. Pattern. Recog, 2005, pp. 947–954.
5. Elden.L, “Partial least squares vs. Lanczos bidiagonalization—I:Analysis of a projection method for multiple regression,” Comput. Statist. Data Anal., vol. 46, no. 1, pp. 11–31, May 2004.
6. L. Elden, “Partial least squares vs. Lanczos bidiagonalization—I:Analysis of a projection method for multiple regression,” Comput. Statist. Data Anal., vol. 46, no. 1, pp. 11–31, May 2004.
7. J. Holappa, T. Ahonen, and M. Pietikainen, “An optimized illumination normalization method for face recognition,” inProc. IEEE Int. Conf. Biometrics: Theory, Appl. Syst., 2008, pp. 1–6.
8. G. Aggarwal, S. Biswas, and R. Chellappa, “UMD experiments with FRGC data,” inProc. Comput. Vis. Pattern Recog. Workshop, 2005, pp. 172–178.
9. P. Shih and C. Liu, “Evolving effective color features for improving FRGC baseline performance,” inProc. Comput. Vis. Pattern Recog.Workshop, 2005, pp. 156–163.
10. V. Ojansivu, E. Rahtu, and J. Heikkilä, “Rotation invariant local phase quantization for blur insensitive texture analysis,” inProc. IEEE Int. Conf. Pattern Recog., 2008, pp. 1–4.

11. C. Liu, “Capitalize on dimensionality increasing techniques for improving face recognition grand challenge performance,”IEEE Trans.Pattern Anal. Mach. Intell., vol. 28, no. 5, pp. 725–737, May 2006. FRGC data,” in Proc. Comput. Vis. Pattern Recog. Workshop, 2005, pp. 172–178.
12. P. Shih and C. Liu, “Evolving effective color features for improvingFRGC baseline performance,” in Proc. Comput. Vis. Pattern Recog.Workshop, 2005, pp. 156–163.
13. V. Ojansivu, E. Rahtu, and J. Heikkilä, “Rotation invariant local phase quantization for blur insensitive texture analysis,” in Proc. IEEE Int. Conf. Pattern Recog., 2008, pp. 1–4.
14. C. Liu, “Capitalize on dimensionality increasing techniques for improving face recognition grand challenge performance,” IEEE Trans.Pattern Anal. Mach. Intell., vol. 28, no. 5, pp. 725–737, May 2006.
15. J. Wright, A. Y. Yang, A. Ganesh, S. S. Sastry, and Y. Ma, “Robust face recognition via sparse representation,” IEEE Trans. Pattern Anal.Mach. Intell., vol. 31, no. 2, pp. 210–227, Feb. 2009.
16. Y. Lui and J. Beveridge, “Grassmann registration manifolds for face recognition,” in Proc. Eur. Conf. Comput. Vis., 2008, pp. 44–57.
17. X. Tan, S. Chen, Z. Zhou, and F. Zhang, “Face recognition from a single image per person: A survey,” Pattern Recognit., vol. 39, no. 9, pp. 1725–1745, Sep. 2006
18. T. Ojala, M. Pietikainen, and T. Maenpaa, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 7, pp. 971–987, Jul. 2002.
19. Z. Cao, Q. Yin, X. Tang, and J. Sun, “Face recognition with learningbased descriptor,” in Proc. IEEE Conf. Comput. Vis. Pattern Recog., 2010, pp. 2707–2714.
20. N. Pinto and D. Cox, “Beyond simple features: A large-scale feature approach to unconstrained face recognition,” in Proc. Int. Conf. Autom. Face Gesture Recog., 2011, pp. 8–15.
21. L.Wolf, T. Hassner, and Y. Taigman, “Descriptor based methods in the wild,” in Proc. Real-Life Images Workshop Eur. Conf. Comput. Vis., 2008.
22. N.-S. Vu and A. Caplier, “Face recognition with patterns of oriented edge magnitudes,” in Proc. Eur. Conf. Comput. Vis., 2010, pp. 313–326.

23. J. Holappa, T.Ahonen, andM. Pietikainen, “An optimized illumination normalization method for face recognition,” in Proc. IEEE Int. Conf. Biometrics: Theory, Appl. Syst., 2008, pp. 1–6.
24. G. Aggarwal, S. Biswas, and R. Chellappa, “UMD experiments with FRGC data,” in Proc. Comput. Vis. Pattern Recog. Workshop, 2005, pp. 172–178.
25. P. Shih and C. Liu, “Evolving effective color features for improving FRGC baseline performance,” in Proc. Comput. Vis. Pattern Recog. Workshop, 2005, pp. 156–163.
26. V. Ojansivu, E. Rahtu, and J. Heikkilä, “Rotation invariant local phase quantization for blur insensitive texture analysis,” in Proc. IEEE Int. Conf. Pattern Recog., 2008, pp. 1–4.
27. C. Liu, “Capitalize on dimensionality increasing techniques for improving face recognition grand challenge performance,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 5, pp. 725–737, May 2006.
28. J. Wright, A. Y. Yang, A. Ganesh, S. S. Sastry, and Y. Ma, “Robust face recognition via sparse representation,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 31, no. 2, pp. 210–227, Feb. 2009.
29. Y. Lui and J. Beveridge, “Grassmann registration manifolds for face recognition,” in Proc. Eur. Conf. Comput. Vis., 2008, pp. 44–57.[30] X. Tan, S. Chen, Z. Zhou, and F. Zhang, “Face recognition from a single image per person: A survey,” Pattern Recognit., vol. 39, no. 9, pp. 1725–1745, Sep. 2006.
30. J. Liu, S. Chen, Z. Zhou, and X. Tan, “Single image subspace for face recognition,” in Proc. IEEE Int. Conf. Autom. Face Gesture Recog., 2007, pp. 205–219.
31. F. De la Torre, R. Gross, S. Baker, and V. Kumar, “Representational oriented component analysis (ROCA) for face recognition with one sample image per training class,” in Proc. IEEE Conf. Comput. Vis. Pattern Recog., 2005, pp. 266–273.
32. K. I. Diamantaras and S. Y. Kung, Principal Component Neural Networks: Theory and Applications. New York: Wiley, 1996.
33. M. Aly, P.Welinder, M. Munich, and P. Perona, “Scaling object recognition: Benchmark of current state of the art techniques,” in Proc. IEEE Conf. Comput. Vis. Workshop, 2009, pp. 2117–2124.

34. Q. Yuan, A. Thangali, and S. Sclaroff, "Face identification by a cascade of rejection classifiers," in Proc. Comput. Vis. Pattern Recog. Workshop, 2005, pp. 152–159.
35. G.-D. Guo and H.-J. Zhang, "Boosting for fast face recognition," in Proc. Int. Conf. Comput. Vis. Workshop, 2001, pp. 96–100.
36. N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in Proc. IEEE Conf. Comput. Vis. Pattern Recog., 2005, pp. 886–893.
37. J. G. Daugman, "Uncertainty relation for resolution in space, spatial frequency, and orientation optimized by two-dimensional visual cortical filters," J. Opt. Soc. Amer. A, Opt. Image Sci., vol. 2, no. 7, pp. 1160–1169, Jul. 1985.
38. L. Elden, "Partial least squares vs. Lanczos bidiagonalization—I:Analysis of a projection method for multiple regression," Comput. Statist. Data Anal., vol. 46, no. 1, pp. 11–31, May 2004.
39. R. Rosipal and N. Kramer, "Overview and recent advances in partial least squares," in Proc. SLSFS, 2006, vol. 3940, Lecture Notes in Computer Science, pp. 34–51.
40. K. Delac, M. Grgic, and S. Grgic, "Independent comparative study of PCA, ICA, and LDA on the FERET data set," Int. J. Imaging Syst. Technol., vol. 15, no. 5, pp. 252–260, 2005.