JOURNAL OF ENGINEERING AND TECHNOLOGY, Vol. 11 December 2013 ISSN 1684-4114
http://www.iutoic-dhaka.edu/jet

Vision Inspired Adaptive Local Ternary Pattern for Face Recognition and Verification

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Received 15 June 2012; Accepted after revision 30 December 2013

ABSTRACT

Face recognition and verification algorithms use a varity of features that describe a face. Most popular amongst these features are LBP (Local binary pattern) and its varient Local Ternary Pattern (LTP). LBP is very sensitive to near uniform region and is incapable of handling intensity actuation that often happens due to noise. This is addressed by introducing a fixed threshold in LTP. However, a xed threshold often fails to perfectly describe a feature. To address this issue, we propose an adaptive LTP (ALTP) that extends LTP to evoke vibrant threshold. To verify the proposed methods we have used a recent challenging face database named Label Face in Wild (LFW). Our proposed ALTP method is light weight, and achieved an accuracy of 76.23%, which is impressive in contrast to other computationally inexpensive state of the art methods.

Keywords: *Binary Pattern, Ternary Pattern.*

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can be categorized in three broad categories such as: *Holistic based approaches*, *Feature based approaches* and *Hybrid approaches*. Among these approaches theLBP [2, 3] based Holistic approaches became popular for being simple in terms of computational complexity and higher accuracy. We, thus, describe the basics of LBP and its variant LTP first and then briefly summarize different methods that fall into these three categories in the subsequent subsections.

Table 1: Summary of holistic based face recognition methods - I

Author	Publication year	Dataset	Methods	Classifier	Highest Accuracy
Conrad Sanderson, Brian C. Lovell [7]	2009	LFW	2D DCT	Multi-Region Histogram (MRH)	72.95%
Conrad Sanderson, Brian C. Lovell [7]	2009	LFW	2D DCT	PCA	59.82%
Conrad Sanderson, Brian C. Lovell [7]	2009	LFW	2D DCT	Randomized Binary Tree (RBT)	72.45%
Conrad Sanderson, Brian C. Lovell [7]	2009	FERET	2D DCT	Multi-Region Histogram (MRH)	89%
Conrad Sanderson, Brian C. Lovell [7]	2009	FERET	2D DCT	PCA	65%
Savvides .M, Abiantun, Heo, Park, Xie, Vijayakumar, B.V.K.[8]	2006	FRGC-2	Kernel Corelation Feature Analysis (KCFA)	SVM	87.50%
Savvides .M, Abiantun, Heo, Park, Xie, Vijayakumar, B.V.K.[9]	2006	FRGC-2	DCT	SVM	91.33%
Xiaoyuan Jing, Qian Liu, Chao Lan[10]	2010	FRGC-2	Holistic Orthogonal Analysis (HOA)and PCA	Fisher Criterion	67.06%
		AR			81.04%

Table 2: Summary of Holistic based face recognition methods - II

Author	Publication year	Dataset	Methods	Classifier	Highest Accuracy
Papa J.P, Falcao[11]	2009	ORL	PCA	Optimum Path Forest(OPF)	96.84 ± 0.56%
				SVM	98.17 ± 1.00%
				ANN-MLP	64.00 ± 1.86%
		CBCL	PCA	Optimum Path Forest(OPF)	84.73 ± 0.56%
				SVM	86.63 ± 0.52%
				ANN-MLP	74.25 ± 1.24%
X. Tan and B. Triggs[4]	2007	FRGC-104	LBP/X2	Distance Transform based similarity metric (DT)	41.6%
			PP+LBP/X2		79%
			PP+LTP/X2		80.4%
			PP+LTP+DT		86.3%
		Extended Yale-B	LBP/X2		44.4%
			PP+LBP/X2		87.5%
			PP+LTP/X2		97.1%
			PP+LBP+DT		95.2%
			PP+LTP+DT		97.2%
		CMU PIE	PP+LTP+DT		100%
J. Write, A. Y. A. Ganesh, S.S. Sastry, and Y. Ma[12]	2009	Extended Yale-B	Eigen	Sparse Representation-based Classification (SRC)	86.5%
			Laplacian		87.49%
			Random		82.6%
			Downsample		74.57%
			Fisher		86.91%
			E-Random		90.72%
		AR Database	Eigen		71.14%
			Laplacian		73.71%
			Random		57.8%
			Downsample		46.78%
			Fisher		86.98%
			E-Random		78.54%

Table 3: Feature based face recognition methods

Author	Publication year	Dataset	Methods	Classifier	Highest Accuracy
Lior Wolf, Tal Hassner, and Yaniv Taigman [1]	2011	LFW	LBP Gabor (C1) TPLBP FPLBP SIFT	SVM	67.82% 62.87% 68.90% 68.20% 68.70%
Savvides M, Abiantun, Heo, Park, Xie, Vijayakumar, B.V.K.[8]	2006	FRGC-2	Eye Region	SVM	83.50%
G. Hua and A. Akbarzadeh [13]	2009	LFW Yale ORL PIE AR	Part Based Face Representation	Robust Elastic and Partial Matching Metric	60% $90.6 \pm 3.1\%$ $99.4 \pm 0.9\%$ $98.6 \pm 0.2\%$ 81.04%

Table 4: Hybrid face recognition methods

Author	Publication year	Dataset	Methods	Classifier	Highest Accuracy
Lior Wolf, Tal Hassner, and Yaniv Taigman [1]	2011	LFW	LBP + Gabor(C1) +TPLBP + FPLBP	SVM	70.62%
Lior Wolf, Tal Hassner, and Yaniv Taigman [1]	2011	LFW	LBP + Gabor (C1)+ TPLBP + FPLBP+ SIFT	SVM	71.93%
Savvides .M, Abiantun, Heo, Park, Xie, Vijayakumar, B.V.K.[8]	2006	FRGC-2	KCFA and Eye Region	SVM	90%

2.1 LBP and LTP

Local Binary Pattern (LBP) [14] is an n-bit binary code at a pixel, c, in a gray scale image is generated by Equation 1, which compares c's intensity with that of its n neighbors. These neighbors are located at uniform distances on a circle centered at c with radius r:

$$LBP_{n,r}(x_c, y_c) = \sum_{l=0}^{n-1} q(g_l - g_c)2^l,\ q(a) = \begin{cases} 1 & if\ a \geq 0 \\ 0 & otherwise \end{cases} (1)$$

where (x_c, y_c) is the pixel co-ordinate of c, g_c and g_l are the intensities of c and the l^{th} neighboring pixel, respectively. The LBP codes can represent texlets such as edge, corner and line-end.

An LBP is defined as uniform local binary pattern (ULBP) if there are at most two bit transitions in its binary equivalent [14]. In other words, for a uniform pattern, the value of *U(.)* in Equation 2 can be at most 2:

$$U(LBP_{n,r}(x_c, y_c)) = |q(g_{n-1} - g_c) - q(g_0 - g_c)| + \sum_{l=0}^{n-1} |q(g_l - g_c) - q(g_{l-1} - g_c)| (2)$$

For example, 11100011 is a uniform pattern, while 11101011 is not. When uniformity is taken into consideration, all the non-uniform patterns are accumulated in a single bin during histogram formation. With $n = 2$, there are 58 different uniform patterns, and hence the histogram will contain 59 bins in total.

Local Ternary Pattern (LTP) [4] mainly follows the same spirit of LBP. The key di erence is that it introduces a new bit to manage the intensity fluctuations. Thus, LTP becomes a ternary code at a pixel c, which is generated by Equation 3:

$$LTP_{n,r}(x_c, y_c) = \sum_{l=0}^{n-1} q(g_l - g_c)3^l,\ q(a) = \begin{cases} 1 & if\ a \geq \alpha \\ -1 & if\ a \leq \alpha (3) \\ 0 & otherwise \end{cases}$$

Here, the value of α is set to 5. To reduce the size of the feature vector, an LTP code is usually split into two binary codes (upper pattern and lower pattern). For an image, two histograms are built separately for the two types of codes to represent the feature vector of that image. Tan et al. [4] also performed some preprocessing before the code generation, such as Difference of Gaussian ltering (DoG) ltering, gamma correction, illumination normalization and masking.

2.2 Face recognition approaches

In holistic based approaches the features of the entire face is extracted and used as a single vector for classification. In this approach, the face is usually divided to a number of non-zero blocks. Di erent types of features such as: Gabor jet, LBP, LTP, etc. are extracted and used as a whole for veri cation and/or recognition purposes. Among the holistic approaches, *Eigenface*[15] and *Fisher-faces* [16, 17], *LBP*[2, 3], *LTP* [4] based face recongition produced competitive results.

Recently Wright et. al. [12] proposed a new approach named 'Sparse Representation-based Classi cation (SRC)', which is based on the compressed sensing theory [18]. This approach uses sparse features for recognition, and thereby can better handle occulation. Among the recent feature based approaches, authors in [7] proposed a scalable face matching algorithm capable of dealing with faces subject to several concurrent and uncontrolled factors, such as variations in pose, expression, illumination, as well as scale and misalignment problems.

Feature based approaches use local face-features such as eyes, nose, mouth, chin and head outline. These features can be used to uniquely identify the individuals. Methods described in [19, 13] present fearute based approaches. However, the major challenge in feature based approach is that the recognition process is generally e ected by the error-proneness of the features. This is because, most of the times it is di cult to identify the exact fuducial points on a face. Hybrid approach is a combination of holistic and feature based approaches. The hybrid approaches use both local features and the whole face region to recognize a face. Authors in [20] proposed an approach to automatic face recognition. A new framework for extracting facial features based on the *bag of words* method has been proposed in [21] and applied to face and facial expression recognition.

Table 1, 2, 3 and 4 presents a comparative study on the state of the art algorithms for face recognition and veri cation. It can be observed from the tables that the results of almost all face recognition or veri cation approaches degrade when using challenging real life data sets compared to the performance using datasets from controlled environments. Developing a descriptor worthy of overcoming hardles imposed by real life images is a challenging and interesting area of research; and this is the challenge we address in this paper. Furthermore, we choose holistic LBP-based based method, as long as it is light weight and produce competitive accuracies.

3 ADAPTIVE LOCAL TERNARY PATTERN (ALTP)

In general a feature based holistic face verification system consist of three parts: *face detection, feature extraction* and *feature grouping and classification*. This process is summarized in Figure 1. We adapted a similar process for our research.

3.1 Feature Extraction

Human eye cannot distinguish intensity variation on the surface of an object beyond a constant contrast difference, even though human can recognize it well. This property is known as *Weber's law*. The *Weber's law* is described by $\frac{\Delta I}{I} = k$

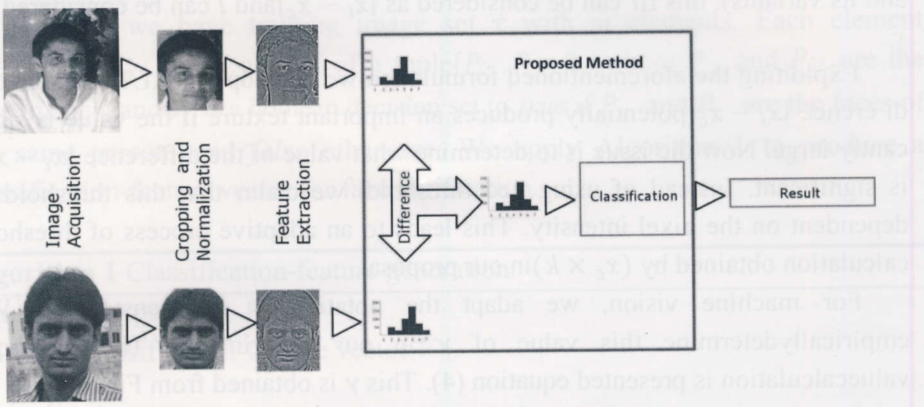

Figure 1: The overview of full face verification system

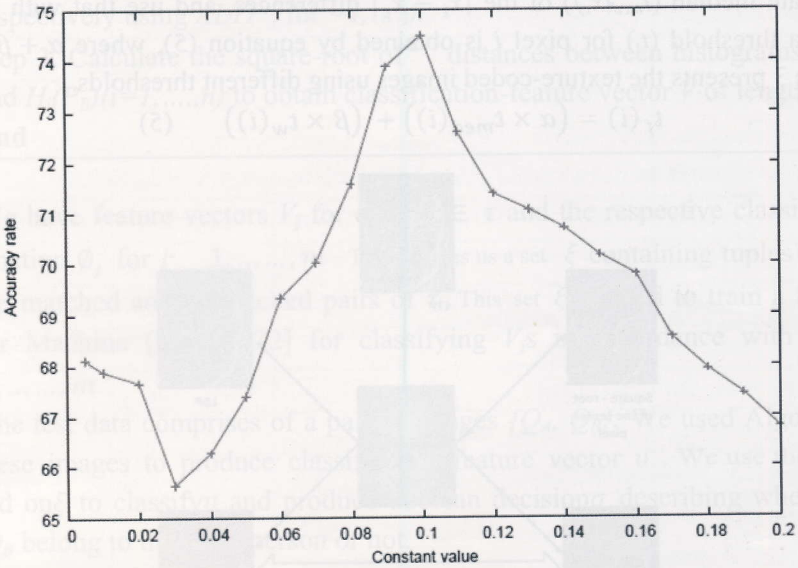

Figure 2: Change of constant value vs accuracy rate

where ΔI is a noticeable difference for discrimination, I represents the initial stimulus intensity and k remains constant despite variations in the I term. Inspired by the human vision system we assume that a xed amount of intensity variation is not necessary to identify an object. Thus, while calculating the di erence between the center pixel intensity (x_c) to its neighbors (x_i) (in case of LBP and its variants), this ΔI can be considered as $|x_i - x_c|$and I can be considered as x_c.

Exploiting the aforementioned formulation we develop our ALTP, where the di erence $|x_i - x_c|$potentially produces an important texture if the value is signi cantly large. Now the issue is to determine what value of the difference $|x_i - x_c|$ is significant. Instead of using xed threshold, we claim that this threshold is dependent on the pixel intensity. This leads to an adaptive process of threshold calculation obtained by $(x_c \times k)$in our proposal.

For machine vision, we adapt the notation γ for constant k. We empiricallydetermine this value of γ in our experiments. The threshold valuecalculation is presented equation (4). This γ is obtained from Figure 2.

$$t_w(x_c) = x_c \times \gamma (4)$$

Figure 2 presents a line graph reaching to the peak value of face recognition accuracy using $\gamma = 0.1$. Further to reduce the impact of random noise we calculate median $(t_{med}(x_c))$ of the $|x_i - x_c|$ differences, and use that with $t_w(x_c)$. Thus a threshold (t_f) for pixel i is obtained by equation (5), where $\alpha + \beta = 1$. Figure 3 presents the texture-coded images using different thresholds.

$$t_f(i) = (\alpha \times t_{med}(i)) + (\beta \times t_w(i)) \qquad (5)$$

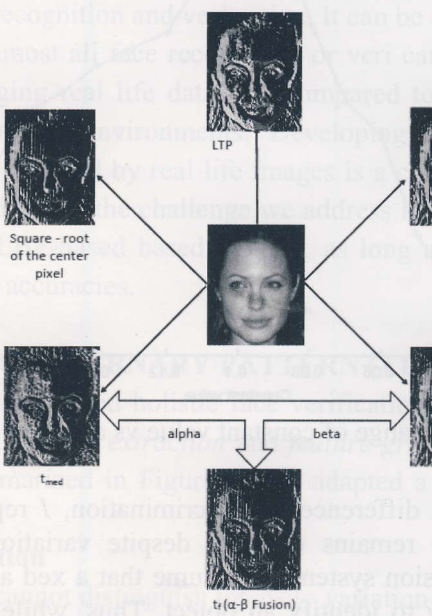

Figure 3: Images of LBP varients with different threshold value

3.2 Feature Classification

Suppose we have training image set τ with m elements. Each element $P \in \tau$ $(j \quad 1, \dots \dots, m$ consist of a tuple$\{P \;, P \;, \emptyset_j$ where P and P are the face images, and$\emptyset_j$ is a boolean decision set to *true* if P and P are the faces of the same person, and *false* otherwise. We apply Algorithm 1 to produce a classification-feature vector for face verification.

Algorithm 1 Classification-feature generation

Input: Image pair $\{P_A, P_B\}$

Output: Classification-feature vector V

Begin

Step 1. Divide P_A and P_B into n blocks $B_i(P_A)$, $B_i(P_B)$ respectively for $i=1, \dots, n$

Step 2. Calculate histograms $H_i(P_A)$, $H_i(P_B)$ for each block $B_i(P_A)$, $B_i(P_B)$ respectively using *ALTP* , for $=1, \dots, n$

Step 3. Calculate the square-root of^2 distances between histograms $H_i(P_A)$ and $H_i(P_B)(i=1, \dots, n)$ to obtain classification-feature vector V of length n.

End

We have feature vectors V_j for each $P \in \tau$ and the respective classification information $\emptyset_j$ for $j \quad 1, \dots \dots, m$ This is gives us a set ξ containing tuples $\{V \;, \emptyset_j$ for the matched and unmatched pairs of τ . This set ξ is used to train a Support Vector Machine (SVM) [22] for classifying V_js in accordance with $\emptyset_j$ for $j \quad 1, \dots \dots, m$.

The test data comprises of a pair of images $\{Q_A, Q_B\}$. We used Algorithm 1 on these images to produce classification-feature vector υ We use the SVM trained onξ to classifyυ and produce boolean decisionσ describing whether Q_A and Q_B belong to the same person or not.

4 EXPERIMENTAL RESULTS

In this section, we present comprehensive experimental evaluation of the proposed method using Labeled Faces in the Wild (LFW) [6] dataset for studying face verification in unconstrained environments and compared our results with previous approaches.

In the dataset there are two parts: View 1 for training the algorithm and in View 2 is for calculating the performance. View consists of 1100 matched

1100 mismatched pairs of images as training data. And there are 500 matched and mismatched pairs each comprise the test data. View 2 has 10 set of data, each carrying 300 pairs of images. We used ten fold cross validation as suggested in the database.

The main goal of this research is to achieve an adaptive threshold value for generating texture feature, which is able to generate same code for same feature for two di erent images of a person irrespective of noisy intensity uctuations and monotonic illumination variation. For generating the code we have used $n = 8$ and $r = 2$, uniform pattern for all the methods, and no preprocessing has been performed. Table 5 presents results of the three proposed methods using LFW dataset (View 2).

Table 5: Accuracy rate of proposed methods

Methods for Threshold in Feature Extraction	Accuracy in %
Weber (t_w)	74.85%
Median (t_{med})	74.67 %
ALTP (t_f)	76.23%

Table 6: Some State-of-the-art Accuracy on LFW Dataset

Approach/Method	Accuracy
LTP, funneled	0.7112 ±0.0045
Eigenfaces, original [23]	0.6002 ±0.0079
Nowak, original [24]	0.7245 ± 0.0040
Nowak, funneled [25]	0.7393 ± 0.0049
Hybrid descriptor-based, funneled [26]	0.7847 ± 0.0051
3x3 Multi-Region Histograms (1024) [7]	0.7295 ± 0.0055
Pixels/MKL, funneled [27]	0.6822 ± 0.0041
ALTP, funneled	0.7623 ± 0.0056

Keeping all the parameters same we compare the proposed methods with LTP as presented in Table 6. We observe that ALTP performs better than the state of the art methods, except Hybrid descriptor-based, in terms of accuracy. The Hybrid descriptor-based method, since is a hybrid method, performs more computation to obtain performance than ALTP. Furthermore, in the original proposal of LTP contains a series of preprocessing steps such as: Difference of Gaussian, Gamma Correction and Contrast Equalization. We observed that using

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