Novel Metric for Local Pattern Histogram for Face Recognition

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Abstract— **The paper will present a novel metric to compute the similarity scores for histograms of local patterns. The results of intensive experiments on two standard face databases, FERET and AT&T, show that the metric are efficient and flexible for real application. It also propose a new implementation to compute similarity scores capable of reducing the time performance and achieve better accuracy rates compared to the current state of art approaches.**

Keywords- Local Binary Pattern, Local Ternary Pattern, Local Derivative Pattern, Histogram, Min score, Chi score.

I. Introduction

Face recognition is one of interesting topics of computer vision because it would have a variety of potential applications such as video surveillance. Like other recognition problems, features are one of important factors to a face recognition system. In early works [1-5], intensity values of pixels have been chosen as features. However, they are often too sensitive to lighting and pose conditions. The accuracy might drop significantly in some extreme conditions. Therefore, finding robust features has become the goal in lots of researches on face recognition. For example, Gabor features, which are extracted using a set of Gabor filters, have been used in recent studies [6]. The authors stated that these features were robust to changes of lighting condition, and their system achieved superior results in intensive experiments. However, these Gabor based methods usually create huge feature vectors. As the result, their systems need significant time performance. In 1996, Ojala *et. al.* [7] invented new features to encode a micro structure of texture called Local Binary Patterns (LBP). Because they contain local texture information, LBP based methods achieved excellent results for texture classification. In 2004, Ahonen *et. al.* [8] used LBP for face recognition. Face images were divided into small rectangles with same size. A similarity of two face images was computed using a sum of scores. Each score for LBP histograms of pair corresponding regions was computed using a metric such as *min*. The authors reported that the method gave outperformed results compared with current methods at that time. Since then, there have been a few of improvements and extensions. Jin *et. al.* [9] proposed local patterns called Improved Local Binary Patterns (ILBP) exploiting information of additional central pixels. Tan and Triggs [10] invented Local Ternary Patterns (LTP). They use three digits or states instead of two ones to encode local texture information. Recently, Jang *et. al.* [11] have proposed novel patterns called Local Derivative Patterns (LDP) investigating higher relationship of local patterns. However, these approaches face two problems. The first problem is the number of labels of patterns. These methods tend to significantly increase the amount of labels. In particular, ILBP need 2^9 labels; LTP has 3^8 ones. Specially, it can reach to 2^{32} labels in LDP based method. As a result, the approaches would create very huge histograms or feature vectors. Therefore, it would take more hardware resources and time performance. To deal with this issue, researchers often decrease a number of bins of histograms. However, it can badly affect the quality of recognition rate. The second issue is a lack of metrics for local pattern histograms. All methods only use *Chi* or *Min* metrics. Therefore, proposing more metrics to measure similarity scores would be necessary. Our study has two purposes. Firstly, we proposed a novel score containing information of both similarity and dissimilarity and having close relationship with probability concept. It is expected to improve accuracy rates. Secondly, we proposed a technique to efficiently represent histograms of labels and relevant algorithms to compute their scores.

The remainder of paper is organized as follows. The next section will review on local patterns and some popular metrics. In section three, we will propose a novel metric as contribution to a set of metrics; moreover, we will use a compact representation for histogram to solve the problem on a number of labels and implement algorithms to compute their scores indirectly. The section four will present our intensive experiments on two public data sets AT&T and FERET. The last section will give the brief review on our study and future works.

II. Reviews on Local Patterns and Their Applications for Face Recognition

In this section, we review LBP and its application for face recognition. LBP was invented by Ojala *et. al* [7]. It is a powerful method to encode the structure of texture due to its robust to illumination and pose. To compute the LBP label for pixel, the intensity value of pixel is compared to its surrounding pixels. Figure 1 shows how to determine LBP label in detail. LBP based methods have been improved and extended since then. LBP was applied by Ahonen *et. al.* [8, 12] to face recognition. Figure 2 shows a three step framework of LBP based face recognition. Step 1 is to determine LBP labels images; then maps of LBP labels are divided into regular rectangles with same size denoted as $\{R_1, R_2, \ldots, R_N\}$ to investigate the local information. Step 2 is to determine histograms of LBP labels for rectangles. In Step 3, each pairs of corresponding histograms are scored by using one of metrics, *Chi* or *Min* (See Equation 1 and 2). Finally, the total score, a sum of scores, is used to measure the similarity between two images. Two popular metrics, *Min* and Chi, have difference originals. *Min* comes from geometry; it is particularly an intersection area of two histograms, measuring their shared area or similarity. However, it does not contain difference information. Otherwise, *Chi* is from statistics, measuring dissimilarity. C*hi* requires more time performance than *Min*, so the latter is often preferred in applications needing high speed performance.

$$s_{min}(\mathbf{X},\mathbf{Y}) = \sum_{i=1}^{N} \min(X_i, Y_i) \qquad (1)$$

$$s_{chi}(\mathbf{X},\mathbf{Y}) = \sum_{i=1}^{N} \frac{(X_i - Y_i)^2}{X_i + Y_i} \qquad (2)$$

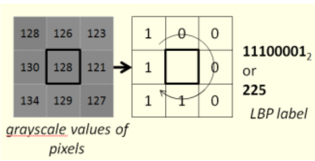

Figure 1. How to determine LBP label for central pixel

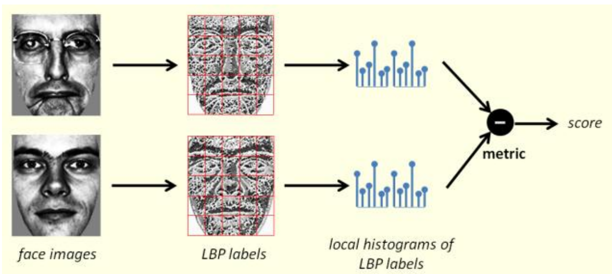

Figure 2. Framework for LBP based face recognition

III. Proposed Similarity Score

In this section, we will present our novel score called *Ratio* to measure a similarity between two histograms and compact representation for histograms and relating algorithms. *Ratio* score is a number representing a ratio between intersection area and union area. We define it as the following:

$$s_{ratio}(\mathbf{X},\mathbf{Y}) = \frac{\sum_{i=1}^{N} \min(X_i, Y_i)}{\sum_{i=1}^{N} \max(X_i, Y_i)} \qquad (3)$$

Figure 3a and 3b shows two histograms $\mathbf{X} = \{3,2,5,1\}$ and $\mathbf{Y} = \{2,4,3,4\}$. Figure 3c shows two areas; the first labeled (1) are same areas and the second labeled (2) are the different areas. Using equation 1, 2 and 3 to determine three scores *Min*, *Chi* and *Ratio*:

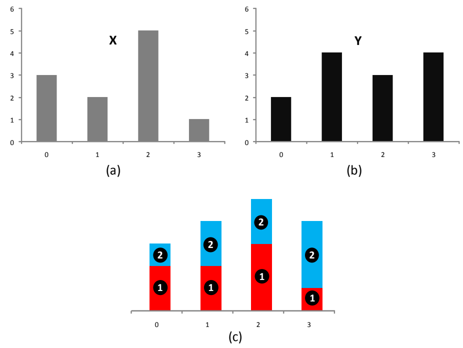

Figure 3. Same and different areas between two histograms **X** and **Y**

$$s_{min}(\mathbf{X},\mathbf{Y}) = \min(3,2) + \min(2,4) + \min(5,3) + \min(1,4) = 8$$

$$s_{chi}(\mathbf{X},\mathbf{Y}) = \frac{(3-2)^2}{3+2} + \frac{(2-4)^2}{2+4} + \frac{(5-3)^2}{5+3} + \frac{(1-4)^2}{1+4} = 3.36$$

$$s_{ratio}(\mathbf{X},\mathbf{Y}) = \frac{\min(3,2) + \min(2,4) + \min(5,3) + \min(1,4)}{\max(3,2) + \max(2,4) + \max(5,3) + \max(1,4)} = 0.5 = 50\%$$

Notice that *Ratio* score says that the similarity between **X** and **Y** is 50% or the probability of **X** and **Y** to be similar is 0.5. It means that *Ratio* score is much more meaningful because it contains a language of probability.

A. *Proposed Compact Histogram Representation*

The number of local pattern labels is limited; therefore, histograms of local pattern labels are discrete numbers which can be represented on integer number line. We create a simple data structure to store histogram which has a list of labels denoted as **L** and a list of their corresponding instances **C** greater than zero.

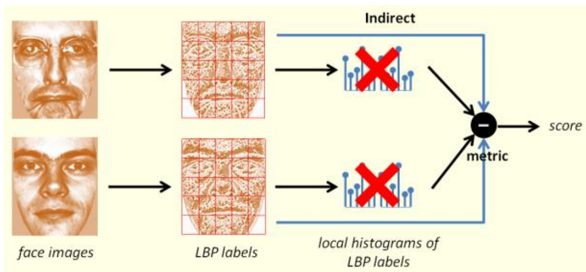

Figure 4. Illustration for implementations

Algorithm 1 (Algorithm to compute compact histogram)

Input: A list of labels **A**

Output: A compact histogram **H** = <**L**, **C**> of **A**

Step 1: Sort **A** in ascending order

Step 2: Find unique labels of **A** called **L**

Step 3: Count the occurrences of labels **L** in **A** called C

The complexity of algorithm is O(nlogn) where n is the number of elements of **A**.

B. Algorithms to Compute Scores

We implement some algorithms to compute scores without using histograms. Figure 4 illustrates our idea. There are two types of algorithms. The first one uses lists of labels to compute scores. The second one converts lists of labels to compact histograms and evaluates scores.

Algorithm 2 (Type 1 Algorithm to compute *Min* score)

Input: Two lists of labels $\mathbf{L}_1$ and $\mathbf{L}_2$

Output: *Min* score s_{min}

Step 1: Sort $\mathbf{L}_1$ and $\mathbf{L}_2$ in ascending order

Step 2: Determine s_{min}

$s_{min} = 0$

n_1 is the length of $\mathbf{L}_1$

n_2 is the length of $\mathbf{L}_2$

$i_1 = 0$

$i_2 = 0$

while ($i_1 < n_1$) **and** ($i_2 < n_2$)

  if $\mathbf{L}_1[i_1] == \mathbf{L}_2[i_2]$ **then**

    s_{min}++

    i_1++

    i_2++

    continue

  end if

  if $\mathbf{L}_1[i_1] < \mathbf{L}_2[i_2]$ **then**

    i_1++

    continue

  end if

  if $\mathbf{L}_1[i_1] > \mathbf{L}_2[i_2]$ **then**

    i_2++

    continue

  end if

end while

O(Algorithm 2) = O(Step 1) + O(Step 2). The complexity of Step 1 is nlogn where n equal to max (n_1, n_2); Step 2 uses only increment and compare operators; therefore its complexity is n. The total complexity is nlogn. The idea can be extended to metric *L1* and s_{max}.

Algorithm 3 (Type 2 Algorithm to compute *Min* score)

Input: Two compact histograms

$\mathbf{H}_1 = \langle\mathbf{L}_1, \mathbf{C}_1\rangle$, $\mathbf{H}_2 = \langle\mathbf{L}_2, \mathbf{C}_2\rangle$

Output: min score s_{min}

$s_{min} = 0$

n_1 is the length of $\mathbf{L}_1$

n_2 is the length of $\mathbf{L}_2$

$i_1 = 0$

$i_2 = 0$

while ($i_1 < n_1$) **and** ($i_2 < n_2$)

  if $L_1[i_1] == L_2[i_2]$ **then**

    s_{min}+= abs($C_1[i_1] - C_2[i_2]$)

    i_1++

    i_2++

    continue

  end if

  if $L_1[i_1] < L_2[i_2]$ **then**

    i_1++

    continue

  end if

  if $L_1[i_1] > L_2[i_2]$ **then**

    i_2++

    continue

  end if

end while

The complexity of algorithm O(Algorithm 3) is n with n equal to min(n_1, n_2).

IV. EXPERIMENTAL DESIGNS

In this section, we will present our experiment designs and results on two standard face dataset AT&T and FERET.

A. Experiments on AT&T data set

AT&T database [13] was taken at the University of Cambridge. It contains 400 images of 40 individuals, 37 males and 7 females. One of them has 10 images with a few variations in illumination, pose and expression. We randomly divided the database into two separate subsets, train and test. The number of images of each set is 200 and each individual has 5 images. We conducted two experiments to compare the accuracy rate and time performance.

We conducted the first experiment to compare the accuracy of *Min*, *Chi* and *Ratio* scores with respect to the size of window or local region. The window size should neither too small nor too large. Because if too small, it would cause the misalignment effects between two corresponding local regions; otherwise, if too large, the regions does not contain local information. Therefore, we set it to {4, 6, 8, 10, 12, 14, 16 and 18}. The experimental results are showed in the Figure 5. As can be seen, in all of cases, the accuracy average values of *Ratio* are always the highest. It reaches to 97.75% corresponding to window size to 18 which is also the optimal window size for two remaining scores.

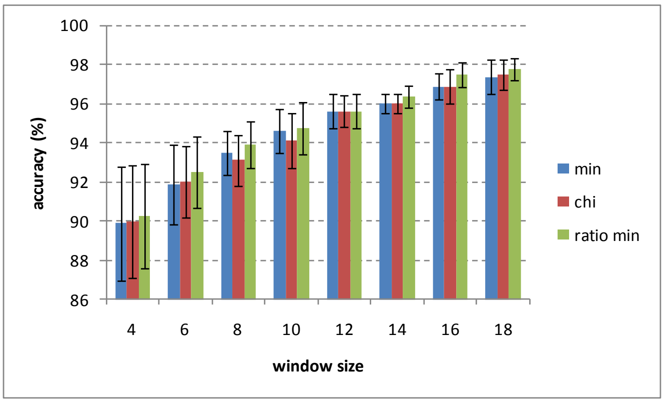

Figure 5. Experimental results on AT&T dataset

B. *Experiments on FERET data set*

Grayscale FERET [14, 15] is standard dataset and is widely used for evaluation. There are more than 14000 images of about 1000 individuals. It contains a lot of subsets. However, we used Gallery subset and four probe subsets FB, FC, DUPI and DUPII.

- Gallery or FA subset contains frontal 1196 images of 1196 people.
- FB subset contains 1195 images. The subjects were asked for an alternative facial expression than in fa photograph.
- FC subset contains 194 images. Its images were taken under different lighting conditions.
- DUPI subset contains 722 images. The photos were taken later in time.
- DUPII subset contains 234 images. This is a subset of the DUPI containing those images that were taken at least a year after the corresponding gallery image.

Based on the information containing in ground truth files, we cropped, aligned to normalize images (130 by 150) and apply histogram equalization on them. We also repeated two kinds of experiments with same purposes.

The first experiment is to measure the ability of each score with respect to the size of window. We set it to {8, 12, 16, 20, 24, 28 and 32}. Figure 6 shows the experimental results. Once again, the *Ratio* metric get the highest accuracy rate in all cases of four probe sets. According to these experiments, the optimal window size is about 12 with respect to balance trade off factors such as accuracy average on four probe sets.

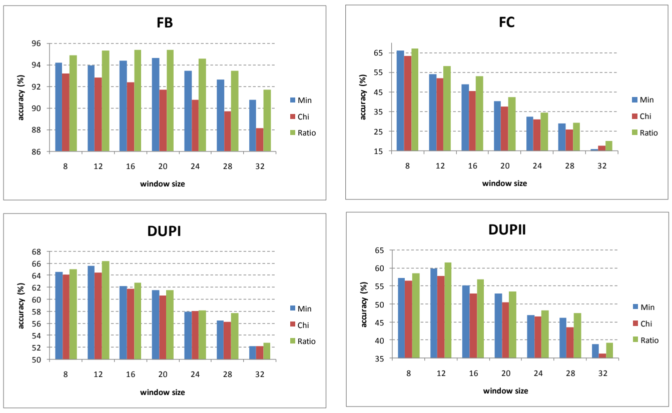

Figure 6. Experimental results on FERET dataset

V. Conclusion

In summary, we proposed a novel metric named *Ratio* score for Local Pattern based methods. It can explain similarities better and clearer than the other metrics under viewpoint of probability. Our intensive experiments on two dataset AT&T and FERET confirmed that our metric is better than current metrics. We also implemented the algorithms to determine scores of histograms but they do not require determining histograms. The algorithms significantly improve the time performance of face recognition system.

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