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An Efficient Real Time Face Detection and Recognition System for Retrieval of videos

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ABSTRACT

A non-parametric descriptor called LBP for efficiently summarizing the local structures of the images. These days the interest and demand has been significantly increased in image processing and computer vision because of the effective results seen on the applications in particularly for facial image analysis. including tasks such as face detec- tion, face recognition, facial expression analysis, demographic classification, etc. This paper has presented a detailed survey on LBP methodology and its types used for various other cases and variations.As a typical application of the LBP approach, LBP-based facial image analysis is extensively reviewed.

Keywords— LBP, ILBP, Facial image analysis, ILBP, MHLVP, Face recognition and Gabor phases.

1. Introduction

During the last few years, Local Binary Patterns (LBP) has interest in image processing and computer vision. As a non- parametric method, LBP summarizes local structures of the images efficiently by comparing each pixel with its neighboring pixels The most important properties of LBP are its tolerance regarding monotonic illumination changes and computational simplicity LBP was originally proposed for texture analysis and has proved a simple yet powerful approach to describe local structures. It extensively exploited the applications, for instance, face image analysis , retrieval of image and video,motion .LBP-based facial image analysis has been one of the most popular and successful applications Facial image analysis is one of the research topic in computer vision, with a important applications, e.g., human-computer interaction, biometric identification LBP make use of facial representation in different works containing face recognization, face detection, a demographic classification like(gender, race, age) and other applications.

The development of LBP methodology can be well demonstrated in facial image analysis, and most of its recent variations are proposed in this. we present a comprehensive survey of the LBP methodology, LBP-based feature selection, as well as the application to facial image analysis. To the best of our knowledge, this paper is the first survey that extensively reviews LBP methodology and its application to facial image analysis, with more than 100 related literatures reviewed.

The original LBP operator labels the pixels of an image with decimal numbers, called Local Binary Patterns or LBP codes, which encode the local structure around each pixel. It proceeds thus, as

illustrated in Fig.1: Each pixel is compared with its eight neighbors in a 3x3 neighborhood by subtracting the center pixel value; The resulting strictly negative values are encoded with 0 and the others with 1; A binary number is obtained by concatenating all these binary codes in a clockwise direction starting from the top-left one and its corresponding decimal value is used for labeling. The derived binary numbers are referred to as Local Binary Patterns or LBP codes.

One limitation of the basic LBP operator is that its small 3x3 neighborhood cannot capture dominant features with large scale structures. To deal with the texture at different scales, the operator was later generalized to use neighborhoods of different sizes [1]. A local neighborhood is defined as a set of sampling points evenly spaced on a circle which is centered at the pixel to be labeled, and the sampling points that do not fall within the pixels are interpolated using bilinear interpolation, thus allowing for any radius and any number of sampling .

2. Literaturesurvey

Aimed at the problems existing in the human facerecognition algorithm, namely the low recognition rate and the image being easily influenced by the factors such as lighting and brightness, this paper has proposed a human face recognition algorithm combining the skin color detection algorithm and binary morphology processing algorithm. First of all, the captured images will go through the YCrCb model detection to reduce the effect of brightness on the image. HSV model detection algorithm has been adopted to reduce the effect of lighting on the image. The detection image gained will be transformed into the binary image. The denoising of binary morphology will be also conducted, thus gaining the human face recognition image. The experimental results show that the algorithm proposed in this paper can achieve the detection and recognition rate of 98.6 percent, 93.3 percent and 90 percent respectively for uncomplicated human face image, relatively complicated human face image and complicated human face image.In another way Morphing attack is becoming a serious challenge for the existing face recognition systems. Aiming at face morphing detection, a novel method is proposed by using Fourier spectrum of sensor pattern noise (FS-SPN). The sensor pattern noise of the facial image is first extracted based on guided image estimation, and the facial quantification statistics, which characterize the specific frequency difference in FS-SPN between the real face image and the morphed image, are obtained. With a linear support vector machine, morphed face image can be detected. Experimental results and analysis show that it outperforms the existing methods in detection accuracy for both complete morphing and splicing morphing.In other way aims to deploy a network that consists agroup of computers connected with a microcomputer with a camera. The system takes images of people, analyze, detect and recognize human faces using image processing algorithms. The system can serve as a security system in public places like Malls, Universities, and airports. It can detect and recognize a human face in different situations and scenarios.This system implements “Boosted Cascade of Simple Features algorithm” to detect human faces. “Local Binary Pattern algorithm” to recognize these faces. Raspberry Pi is the main component connected to a camera for image capturing. All needed programs were written in python. Tests and performance analysis were done to verify the Efficiency.

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3.Objective

CLBP also contains the grey and sign value differences between a provided cental pixels and Itsadjacents in order to enhance discriminative power of the actual LBP operator. Comparison of the absolute value of GD with the provided central pixel in order to generate code similar to LBP, It will be done by CLBP.Unlike the coding strategy of binary bit used by ELBP.

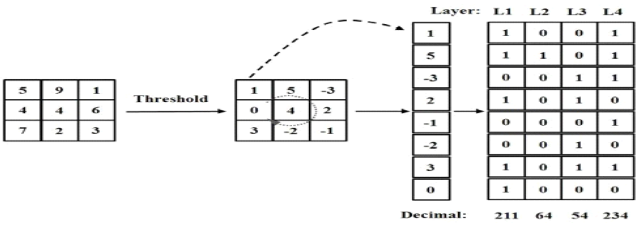

Fig 3 An example of ELBP operator

4. Implementation

4.1 Enhancing the robustness

The operator thresholds exactly at the value of central pixel because LBP is sensitive to noise. In order to solve this problem, the original LBP has been extended new version with 3-value codes, called as Local Ternary Patterns(LTP) . In LTP,indicators*(x)* in (1) is replaced by:

$$s(i_n, i_c, t) = \begin{cases} 1 & i_n \geq i_c + t \\ 0 & |i_n - i_c| < t \\ -1 & i_n \leq i_c - t \end{cases}$$

where*t* is a user-specified threshold. Even though the LBP codes are much resistant to noise, But strictly vary from gray-leveltransformations.Using coding scheme each ternary pattern is

splitted into two parts as positive and negative ones.

The major issue of LTP is that threshold t should be set,which is very complicated.

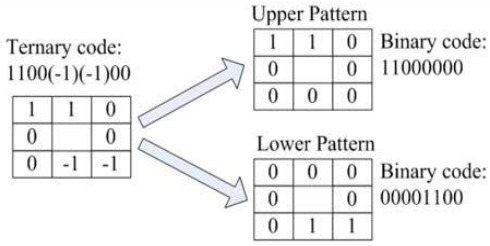

Fig 4 An example of the LTP operator

The Soft LBP (SLBP) was introduced , which employstwo fuzzy membership functionsinstead of (2) for thresholding:

$$s_{1,d}(x) = \begin{cases} 0 & x < -d \\ 0.5 + 0.5\frac{x}{d} & -d \leq x \leq d \\ 1 & x > d \end{cases}$$

$$s_{0,d}(x) = 1 - s_{1,d}(x)$$

The amount of fuzzificationthat the fuzzyfunction performs is controlled by parameter d.

When the local neighborhood consists of P sampling points, the histogram with a uniform pattern operatorhas bins numbered 0, 1, …,*2P*-1.

The contribution of a singlepixel (*xc*, *yc*) to bin *h* of the histogram is:

$$SLBP(x_c, y_c, h) = \prod_{p=0}^{P-1} [b_p(h) \cdot s_{1,d}(i_p - i_c) + (1 - b_p(h)) \cdot s_{0,d}(i_p - i_c)]$$

wherebp(h)∈{0,1} denotes the numerical value of the pth bit of binary representation of h.

With SLBP, each pixel will contributes to multiple bins ,but the over all summation of contribution of a every single pixel to all bins is always 1. Little change in input image causes a small change in output.But loses invariance to monotonic variations and also increases the computation complexity.As with LTP proper value of d should be set.

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4.2 Selecting the neighbourhood

Selecting the neighborhood for LBP-based techniques is very important.Itinvolves the shape of the neighborhood, the number of sampling points, the distribution of thesampling points and the size ofthe neighbourhood.

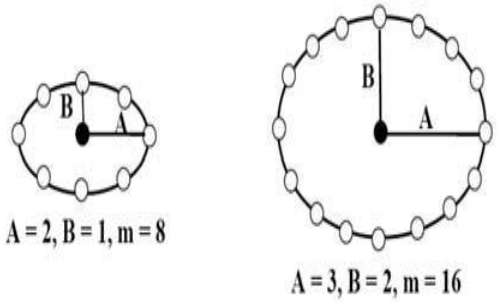


Fig 5 Two examples of Elongated LBP operator

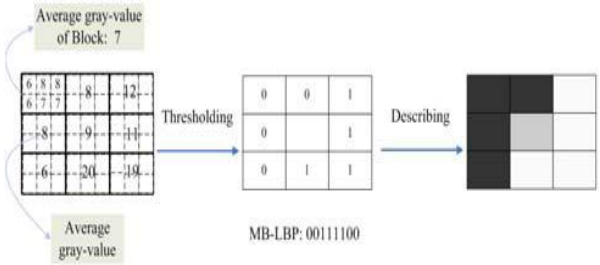
Neighboring pixels in the original LBP are defined on a circle, the reason is to obtain rotation invariance for texture description.But this is not applicable for all, the anisotropic information could also be an important feature.So that Elongated LBP with neighboring pixels lying on an ellipse has been considered.

Fig. 5 gives two examples of the Elongated LBP, where A, B are the long axis and short axis respectively, and m is the number of neighboring pixels. Following original LBP, bilinear interpolation technique is adopted for neighboring pixels that do not fall exactly at the pixels. The Elongated LBP operator could be rotated around the central pixel, with a specific angle to characterize elongated local structures in different orientations, to achieve multi-orientation analysis to caputure both microstructures and macro structures.

Li et al. [8] proposed Multi-Block LBP(MB-LBP) ,which compares average intensities of neighboring sub-regions.

Figure shows an example of MB-LBP, where each sub-region consists of six pixels. A rectangle or a square can be considered as a sub-regions. By using summed-area table [5] or integral image.

The average intensities over the blocks can be computed efficiently. A same scheme is introduced in Three-Patch LBP (TP-LBP) and Four-Patch LBP (FP-LBP) are used to compare distances between the whole blocks (patches) concerned, instead of single pixel [1] or average intensity in [4], and any distance function can be used.



. Fig 6 . An example of the MB-LBP operator

4.3 Extending to 3D LBP

It is very difficult in order to extend the LBP from 2D plane to 3D volume because of equidistant sampling on a sphere is a difficult and also difficult to set an order to thosesampling points, which is important to achieve rotation invariance.

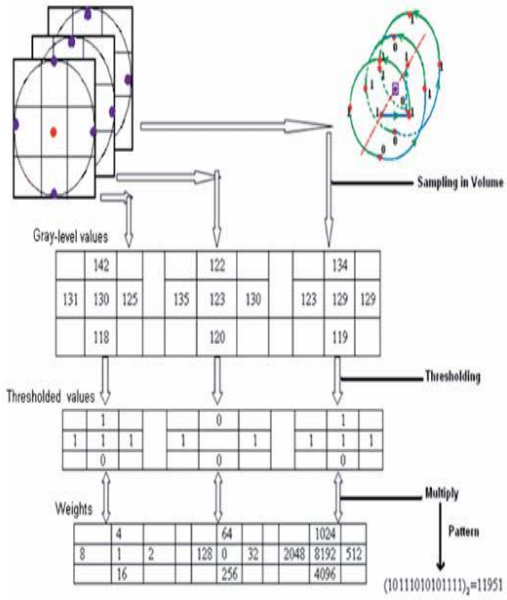


Fig 7 Procedure of *VLBP*

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To endow the LBP with the ability to capture dynamic textureinformation, in [30] and [60], Zhao and Pietikäinen extendedthe LBP neighborhood from 2D plane to 3D space. Theoperator is named as Volume LBP (VLBP or 3D-LBP).

VLBPcombines motion and appearance information, and can thus beused for analyzing image sequences or videos. VLBP not only insensitive to translation and rotation(toward rotations around the *z* axis), but robust to monotonicgrayscale changes as well.

Compared with *LBP (P, R), VLBP (L, P,R)* takes time domain into account, and the parameter *L* denotesthe length of the time interval. From a small local neighborhoodin volume, comparing neighboring pixels with the central pixel,a number of binary units are obtained, and the weights for theseunits are given as a spiral line.

Paulhac *et al*. exploited solution to apply LBP to 3D [9]. They used a numberof circles to represent the sphere, adding the parameter *S*, thusthe operator denotes *LBP(S, P, R)* and they also definedthe uniform rule as in 2D. This method causes the problemthat different textures could have the same LBP description.

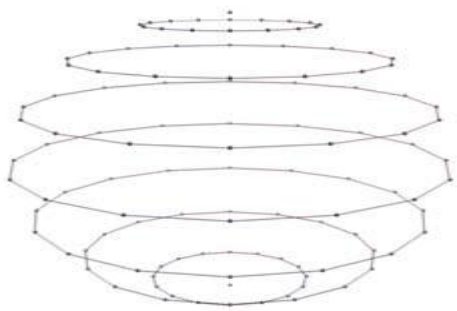

Fig 8 . Representation of a 3D local binary pattern (S=9, P=16, R=2)

Combining with other features

LBP can be combined with other features.For example, Gabor wavelets[6] and LBP features can be combined.Because LBP captures the local appearancedetailGabor wavelet and LBP based features are mutuallycomplementary.while Gabor-wavelets extract shape informationover a broader range of scales.The technique isto first extract Gabor and LBP features in the parallel way, andthen fuse two kinds of features on feature level, matching scorelevel, or decision level[5].

In another technique is first applying Gabor filters and then LBP to the rawimage [4] [7]. By convolving input images with multi-scale andmulti-orientation Gabor filters the Multiple Gabor feature maps (GFM) arecomputed.Each GFM is divided into smallnon-overlapped regions from which LBP histograms are extractedand finally concatenated into a single feature histogram.Multi-resolution Histograms of Local Variation Patterns(MHLVP) [2] as well as Local Gabor Binary Pattern Histogram(LGBPH) [7]-[9], have been proposed based on such aprocedure.

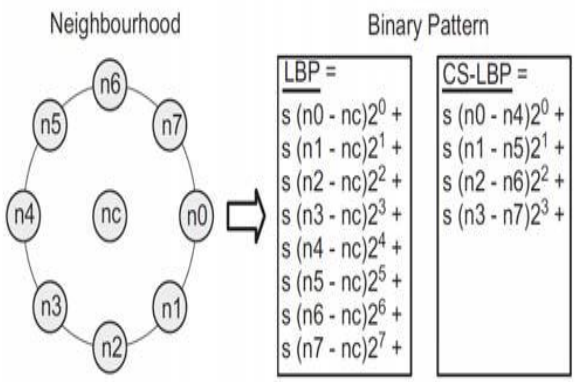

Fig 9. LBP and CS-LBP features for a neighborhood of 8 pixels

A Center-Symmetric LBP (CS-LBP) [7],compares pairs of neighboring pixels which are in the same diameter of the circle.This combines LBP operator with the SIFT [5] definition,which generates binary units than the Original LBP.The differencebetween

CS-LBP and LBP with 8 neighboring pixels is givenin Fig. 9.

4.4 LBP FEATURE SELECTION

In all existing works LBP histograms are extracted from the image which is divided into small regions.Recent trends feature vector lengths have been increased,such as LBP, VLBP and GaborWavelets based LBP.The derived LBP-basedfeature vector provides complete representation withredundant information that should be more compact and discriminative.When we are building real -time system it is important to to have LBP-based representationwith reduced feature length.These issues can be fixed using two categories of techniques the first one is to reduce the feature length based onsome rules (like uniform patterns) and second one is feature selection techniques to choose the discriminative patterns.But first one have less feature selection options,in second one is computationally expensive for off-line training even though feature selectiooncapcity is more.Both have merits and demerits.

4.5 Rule-based Strategy

Uniform pattern is best rule in order to choose LBP features and it has been extensively implemented in real time works.Other than this many rules are available.For example Lahdenoja *et al*.[6]rule which is symmetry level scheme for uniform patterns tofurther reduce the length of LBP feature vectors.The symmetrylevel *Lsym of every pattern is* defined as the minimum of the totalnumber of ones and zeros in that pattern.For example, *Lsym* ofboth patterns (00111111)2 and (00011000)2 are 2.Maximum symmetric patterns will have equal number of ones and zeros,indicating a symmetric edge, while the patterns with thelowest symmetry level are the ones consisting of only ones orzeros.It is proved that the patterns with high symmetry leveloccur more frequently in the images with more discriminativepower [7].It has been concluded that thecomparative performance was obtained using only the patternsof high symmetry level, but the length of feature vectors wasreduced by a quarter.

4.6 Face detection

The main aim of face detection is to identify the placeholders and locations of the facial marks as well as the different sizes of the human faces .Initially LBP was first introduced for detecting the faces. There were low resolution faces also been some times are the cases, so the 4-neighborhood LBP operator ,some times called as LBP(4,1) was used for overlapping tiny facial regions. To discriminate faces from non-faces support vector machine i.e SVM was applied. There are datasets on MIT-CMU were they performed experiments and got a positive result of 221 detected faces from it. Later a proposed hybrid metods were introduced for unfavourable and uncontrainted environments. First the attempt was made to indentify the potential skin regions rather than scanning the whole input image[4].Then the coarse-to-fine methods were deployed to make the scanned regions are faces or not. The whole strategy of this method is firstly the LBP feature vector that is extracted from the scanned region is given as input to the polynomial SVM, the patterns that are not rejected by the first SVM classifier are extracted and analyzed by the second finer and so on. The overall rate of detection of faces from image scanned was 93.4% along with 13 false positives.

There are five measurements detecting faces in colored images and the fact that LBP is constant to monotomic transformations.The five measurements are R,G,B,Y and theta. Using these RGB and Ytheta ,LBP was

utilized to transform these resulted measured values to Histograms.[5] Histograms are a facial description of 23 different spatial templates in order to conserve the shape information of the faces. There thus was develoed heirarchial classifier between histograms and SVM for the detection and discrimination of faces and non-faces.

4.7 Face Recognition

This module aims at identifying the persons or the faces from a digital colored image or a video sequence.Ahonen et al[3] introduced LBP in facial recognition with Nearest Neighbor (NN) classifier and Chi square distance as the dissimilarity measurement. [9] There experiments has been successful and has also overcomed the PCA, EBGM and the Bayesian Intra/Extra-personal Classifiers. But then they investigated whether the results are due to local regions of the image or discriminative capacities. There were three texture descriptor extract features and based on the comparisons with them it was known that the face recognition from LBP for representing faces were confirmed.There has been a new introduction called MHLVP for face detection using histogram intersection.

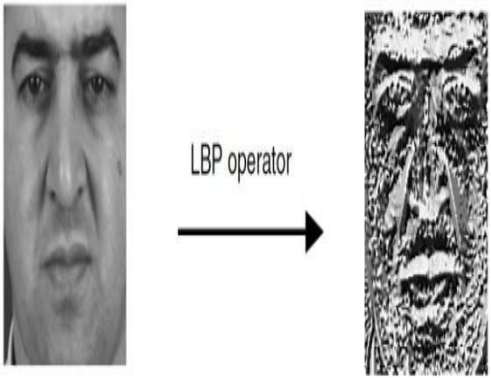

Fig 10 The original image (left)processed by the LBP operator (right).

There were some experiments been conducted on FERET which significantly proved that the algorithms were more efficient than some of the milestone achievemnsts so far. It has believed that there is 97% accuracy achieved on the set of fc with illuminational changes. This was possible because of the implementation of LGBPHS than MHLVP but with more weighted rules. In addition to the FERET database, AR database experiments were also conducted. The results on both of them were promising[7]. Later came the implementation of LGBP with piecewise LDA which not reduces illumination noises but also increases the accuracy on FERET database with the help of domain-partitioning rank boost for selecting the LGBPH features for face recognition. There were subsets generated from the approach namely fb and Dup I from the FERET database and has compared the results with 50% selected features. There was an argument on the Gabor phases on face detection as to by encoding the Gabor phases through LBP and local feature histograms and there were amazing recognition rates obtained on FERET database as 99% for fb, 96% for fc, 78% for DupI and 77% for Dup II.

5. CONCLUSION

The most powerfull descriptor for representing the faces is the LBP. It has many advantages such as monotomic illuminations and computational simplicity. LBP has been deployed successfully in various places such as facial image analysis, biomedical image analysis, aerial image analysis, motion analysis, and image and videoretrieval.

In the amidst of development of LBP method a lot of research has been done in order to expand the scope of the application by increasing the performance as well as robustness among one or two aspects of the original LBP. In order to enhancethediscriminativeability LBP.

ILBP, HammingLBPandELBP are used. LTP and SLBP focus on improving the robustness of LBP on noisy images.Of the most usefull and important application of LBP i.e facial image analysis provides better work and understanding of the application and always tries to improve its abilities.

The following conclusions can be drawn from the approach-

1. local- or component-oriented LBP representations are effective re- presentations for facial image analysis as they encode the in- formation of facial configuration while providing local struc- ture patterns.

2. using the local- or component-oriented LBP facial representations, feature selection is particularly impor- tant for various tasks in facial image analysis, since this facial description scheme greatly increases feature length.

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