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# Face Recognition from Invariant Illumination Based on Textural Analysis and Machine Learning Approach

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***Abstract*— Matching people across multiple camera views known as person re-identification, is a challenging problem due to the change in visual appearance caused by varying lighting conditions. The perceived color of the subject appears to be different with respect to illumination. In this paper, we propose a data driven approach for learning color patterns from pixels sampled from images across two camera views. The intuition behind this work is that, even though pixel values of same color would be different across views, they should be encoded with the same values. We model color feature generation as a learning problem by jointly learning a linear transformation and a dictionary to encode pixel values. Dominant Rotated Local Binary Pattern (DRLBP) have been proposed yields better performance. This paper proposes a novel method of classifying the human face using Convolutional Neural Network.**

***Index Terms*— LBP, DRLBP, FEATURE MATCHING, BINARYIMAGE, FACE DETECTION.**

## I. Introduction

Facial recognition (or face recognition) is a type of biometricsoftware application that can identify a specific individual in a digital image by analyzing and comparing patterns. The Kineticmotion gaming system, for example, uses facial recognition to differentiate among players.Most current facial recognition systems work with numeric codes called faceprints. Such systems identify 80 nodal points on a human face. In this context, nodal points are end points used to measure variables of a person's face, such as the length or width of the nose, the depth of the eye sockets and the shape of the cheekbones. These systems work by capturing data for nodal points on a digital image of an individual's face and storing the resulting data as a faceprint.The faceprint can then be used as a basis for comparison with data captured from faces in an image or video.Facial recognition systems based on faceprints can quickly and accurately identify target individuals when the conditions are favorable. However,if the subject's face is partially obscured or in profile rather than facing forward, or if the light is insufficient,the software is less reliable. Nevertheless, the technology is evolving quickly and there are several emerging approaches, such as 3D modelling, that may overcome current problems with the systemsCurrently, a lot of facial recognition development is focused on Smartphone applications. Smartphone facial recognition capacities include image tagging and other socialnetworking integration purposes as well as personalized marketing. A research team at Carnegie Mellon has developed a proof-of-concept iPhone app that can take a picture of an individual and -- within seconds -- return the individual's name, date of birth and social security number.Facebook uses facial recognition software to help automate user tagging in photographs. Here's how facial recognition works in Facebook: Each time an individual is tagged in a photograph, the software application stores information about that person's facial characteristics. When enough data has been collected about a person to identify them, thesystem uses that information to identify the same face in different photographs, and will subsequently suggest tagging those pictures with that person's name.

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### *A. DIGITALIMAGE PROCESSING*

The identification of objects in an image would probably start with image processing techniques such as noise removal, followed by (low-level) feature extraction to locate lines, regions and possibly areas with certain textures.

The clever bit is to interpret collections of these shapes as single objects, e.g. cars on a road, boxes on a conveyor belt or cancerous cells on a microscope slide. One reason this is an AI problem is that an object can appear very different when viewed from different angles or under different lighting. Another problem is deciding what features belong to what object and which are background or shadows etc. The human visual system performs these tasks mostly unconsciously but a computer requires skilful programming and lots of processing power to approach human performance. Manipulating data in the form of an image through several possible techniques. An image is usually interpreted as a two-dimensional array of brightness values, and is most familiarly represented by such patterns as those of a photographic print, slide, television screen, or movie screen. An image can be processed optically or digitally with a computer.To digitally process an image, it is first necessary to reduce the image to a series of numbers that can be manipulated by the computer. Each number representing the brightness value of the image at a particular location is called a picture element, or pixel. A typical digitized image may have 512 × 512 or roughly 250,000 pixels, although much larger images are becoming common. Once the image has been digitized, there are three basic operations that can be performed on it in the computer. For a point operation, a pixel value in the output image depends on a single pixel value.

### *B. CLASSIFICATIONOF IMAGES:*

There are 3 types of images used in Digital Image Processing. They are-

- Binary Image
- Gray Scale Image
- Color Image

**BINARY IMAGE:**

A binary image is a digital image that has only two possible values for each pixel. Typically the two colours used for a binary image are black and white though any two colors can be used. The color used for the object(s) in the image is the foreground color while the rest of the image is the background color. Binary images are also called bi-level or two-level. This means that each pixel is stored as a single bit (0 or 1).This name black and white, monochrome or monochromatic are often used for this concept, but may also designate any images that have only one sample per pixel, such as grayscale images. Binary images often arise in digital image processing as masks or as the result of Some input/output devices, such as laser printers, fax machines, and bi-level computer displays, can only handle bi-level images

**GRAY SCALE IMAGE:**

A gray scale Image is digital image is an image in which the value of each pixel is a single sample. Images of this sort, also known as black-and-white, are composed exclusively of shades of gray(0-255), varying from black (0) at the weakest intensity to white (255) at the strongest. Grayscale images are distinct from one-bit black-and-white images, which in the context of computer imaging are images with only the two colors, black, and white. Grayscale images have many shades of gray in between. Grayscale images are also called monochromatic, denoting the absence of any chromatic variation. and in such cases they are monochromatic proper when only a given frequency is captured. But also they can be synthesized from a full color image; see the section about converting to grayscale.

**COLOUR IMAGE:**

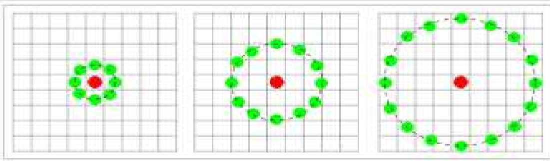
A (digital) color image is a digital image that includes color information for each pixel. Each pixel has a particular value which determines it's appearing color. This value is qualified by three numbers giving the decomposition of the color in the three primary colors Red, Green and Blue. Any color visible to human eye can be represented this way. The decomposition of a color in the three primary colors is quantified by a number between 0 and 255. For example, white will be coded as R = 255, G = 255, B = 255; black will be known as (R,G,B) = (0,0,0); and say, bright pink will be : (255,0,255).

In other words, an image is an enormous two-dimensional array of color values, pixels, each of them coded on 3 bytes, representing the three primary colours. This allows the image to contain a total of 256x256x256 = 16.8 million different colours. This technique is also known as RGB encoding, and is specifically adapted to human vision.It is observable that our behaviour and social interaction are greatly influenced by emotions of people whom we intend to interact with. Hence a successful emotion recognition system could have great impact in improving human computer interaction systems in such a way as to make them be more user-friendly and acting more human-like.

## II. EXISTING APPROACH:

**Local Binary Pattern:**

Local binary pattern(LBP) is a type of visual descriptor used for classification in computer vision. LBP is the particular case of the Texture Spectrum model proposed in 1990. LBP was first described in 1994. It has since been found to be a powerful feature for texture classification; it has further been determined that when LBP is combined with the Histogram of oriented gradients (HOG) descriptor, it improves the detection performance considerably on some datasets. A comparison of several improvements of theoriginal LBP in the field of background subtraction was made in 2015 by Silva et al



Three neighborhood examples used to define a texture and calculate a local binary pattern (LBP)

**Concept:**

The LBP feature vector, in its simplest form, is created in the following manner:

Divide the examined window into cells (e.g. 16x16 pixels for each cell).For each pixel in a cell, compare the pixel to each of its 8 neighbours (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 centre pixel's value is greater than the neighbour's value, write "0". Otherwise, write "1". 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 centre). This histogram can be seen as a 256-dimensional feature vector.Optionally normalize the histogram.Concatenate(normalized) histograms of all cells. This gives a feature vector for the entire window.

The feature vector can now be processed using the Support vector machine or some other machine-learning algorithm to classify images. Such classifiers can be used for face recognition or texture analysis.A useful extension to the original operator is the so-called uniform pattern, which can be used to reduce the length of the feature vector andimplement a simple rotation invariant descriptor. This idea is motivated by the fact that some binary patterns occur more commonly in texture images than others. Alocal binary pattern is called uniform if the binary pattern contains at most two 0-1 or 1-0 transitions. For example, 00010000(2 transitions) is a uniform pattern, 01010100(6 transitions) is not. In the computation of the LBP histogram, the histogram has a separate bin for every uniform pattern, and all non-uniform patterns are assigned to a single bin. Using uniform patterns, the length of the feature vector for a single cell reduces from 256 to 59.Recently, Local Binary Pattern (LBP) and its variantshave been introduced as a feature descriptor for facial expression representation Originally, LBP was introduced for texture analysis.

**System Architecture:**

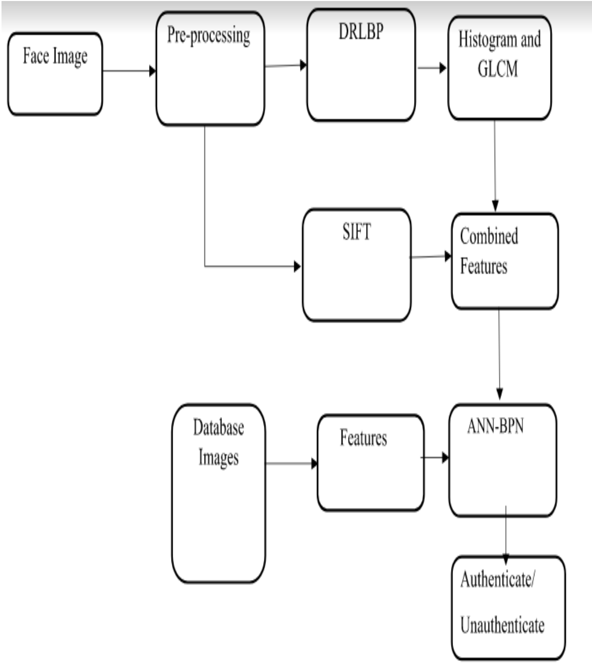



**Fig 1.Block diagram of facial recognition based Person Re-Identification**

## III. FUNCTIONAL MODULES

**Face Detection**

It is process to extract face regions from input image which has normalized intensity and uniform in size. The appearance features are extracted from detected face part which describes changes of face such as furrows and wrinkles (skin texture).In this system model, an executable (.dll- dynamic link library) file is utilized to extract face region.It is used for face detection process is based on hair like features and adaptive boosting method.

**DRLBP Descriptor:**

The descriptor local binary pattern is used to compare all the pixels including the center pixel with the neighboring pixels in the kernel to improve the robustness against the illumination variation. An LBP code for a neighborhood was produced by multiplying the threshold values with weights given to the corresponding pixels, and summing up the result. LBP codes are weighed using gradient vector to generate the histogram of robust LBP and discriminative features are determined from the robust local binary pattern codes. DRLBP is represented in terms of set of normalized histogram bins as local texture features. It is used to discriminate the local edge texture of face invariant to changes of contrast and shape.

**DRLBP Process Flow:**

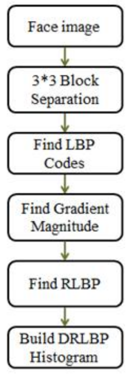



**Fig2. DRLBP Process Flow**

**Gradient Measurement:**

The gradient will be detected from input image to determine the histogram of local binary pattern. Then it will be utilized to find the robust and discriminative features.It involves two descriptors such as, gradient magnitude and orientation. The gradient will be measured in both horizontal and vertical directions with derivative operators.

The gradient magnitude and orientation will be described by,

Magnitude: Gm = Sqrt($F_x$.^2 + $F_y$.^2);

Where, $F_x$ ,$F_y$ = First order derivatives along rows and columns.

**Gradient detection Flow:**

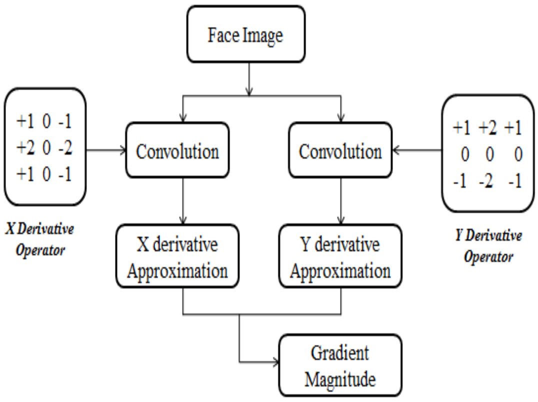



**Fig 3: Gradient detection Flow**

**DR-LBP Features:**

The value of the *ith*weighted LBP bin of a $M \times N$ block is as follows:

$$h_{lbp}(i) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \omega_{x,y} \delta(LBP_{x,y}, i)$$

$$\delta(m,n) = \begin{cases} 1, & m = n \\ 0, & \text{otherwise} \end{cases}$$

The RLBP histogram is created as follows:

$$h_{rlbp}(i) = h_{lbp}(i) + h_{lbp}(2^B - 1 - i), \quad 0 \leq i < 2^{B-1}$$

Where *hrlbp(i )* is the *ith*RLBP bin value. To mitigate the

RLBP issue in Fig. 2, consider the absolute difference between the bins of a LBP code and its complement to form Difference of LBP (DLBP) histogram as follows:

$$h_{dlbp}(i) = |h_{lbp}(i) - h_{lbp}(2^B - 1 - i)|, \quad 0 \leq i < 2^{B-1}$$

Where*hdlbp(i )* is the *ith*DLBP bin value. The number of DLBP bins is 128 for B = 8. Using uniform codes, it is reduced to 30. For blocks that contain structures with both LBP codes and their complements, DLBP assigns small values to the mapped bins. It differentiates these structures from those having no complement codes within the block. The 2 histogram features, RLBP and DLBP, are concatenated to form *Discriminative Robust* LBP (DRLBP) as follows

$$h_{drlbp}(j) = \begin{cases} h_{rlbp}(j), & 0 \leq j < 2^{B-1} \\ h_{dlbp}(j - 2^{B-1}), & 2^{B-1} \leq j < 2^B \end{cases}$$

The after LBP code calculation and apply the image is as given in the fig. The snapshot gives same idea about the local binary pattern classification and histogram are also given.
The query image features will be matched with database image features for the person verification using Euclidean distance metric. It is defined by **Ed=sqrt(sum(Q-Di).^2)**.
Where, Q- Input image features, D- Data feature base, i- No. of samples in database 1 to N

## IV. CONCLUSION:

In this work, we introduced a novel visual attention model that is formulated as a triplet recurrent neural network which takes several glimpses of triplet images of persons and dynamically generates comparative attention location maps for person re-identification. We conducted extensive experimentation three public available person re-identification datasets to validate our method. Experimental results demonstrated that our model outperforms other state-of-the-art methods in most cases, and verified that our comparative attention model is beneficial for the recognition accuracy in person matching.

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