International Journal for Innovative Engineering and Management Research
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IJIEMR Transactions, online available on 26th Jan 2019. Link :
http://www.ijiemr.org/main/index.php?vol=Volume-08&issue=ISSUE-01

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Volume 08, Issue 01, Pages: 226–236.

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International Journal for Innovative Engineering and Management Research
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FAST TEXTURE DATA EMBEDDING METHOD USING ADAPTIVE PIXEL PAIR MATCHING & NOISE REDUCTION

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ABSTRACT: This paper proposes a new facts-hiding technique based totally on pixel pair matching (PPM). The simple concept of PPM is to apply the values of pixel pair as a reference coordinate, and seek a coordinate within the community set of this pixel pair in line with a given message digit. The pixel pair is then changed through the searched coordinate to hide the digit. Exploiting amendment path (EMD) and diamond encoding (DE) are facts-hiding methods proposed recently based totally on PPM. The maximum ability of EMD is 1.161 bpp and DE extends the payload of EMD by way of embedding digits in a larger notational system. The proposed approach gives lower distortion than DE with the aid of imparting extra compact community sets and allowing embedded digits in any notational machine. Compared with the most suitable pixel adjustment process (OPAP) technique, the proposed approach continually has lower distortion for various payloads. Experimental results display that the proposed approach not only offers better overall performance than the ones of OPAP and DE, but also is relaxed underneath the detection of some famous stage analysis techniques.

KEYWORDS: Local binary pattern; Gaussian filters; images; data set; robustness;

I. INTRODUCTION

Texture is a fundamental characteristic of the appearance of virtually all natural surfaces and is ubiquitous in natural images. Texture classification, as one of the major problems in texture analysis, has received considerable attention during the past decades due to its value both in understanding how the texture recognition process works in humans as well as in the important role it plays in the field of computer vision and pattern recognition [1]. Typical applications of texture classification include medical image analysis and understanding, object recognition, content-based image retrieval, remote sensing, industrial inspection, and document classification. The texture classification problem is conventionally divided into the two subproblems. It is generally agreed that the extraction of powerful texture features is of more importance to the success of texture classification and, consequently, most research in texture classification focuses on the feature extraction part [1], with extensive surveys [1]. Nevertheless it remains a challenge to design texture features which are computationally efficient, highly discriminative and effective, robust to imaging environment changes (including changes in illumination, rotation, view point, scaling and occlusion) and insensitive to noise. Recently, the Bag-of-Words (BoW) paradigm, representing texture images as histograms over a discrete vocabulary of local features, has proved effective in providing texture features [2]–[7]. Representing a texture image using the BoW model typically involves the following three steps:

(i) Local texture descriptors: extracting distinctive and robust texture features from local regions;

(ii) Text on dictionary formulation: generating a set of representative vectors (*i.e.,* textons or dictionary atoms) learned from a large number of texture features;
(iii) Global statistical histogram computation: representing a texture images statistically as a compact histogram over the learned text on dictionary.

a) Existing system:

Among local texture descriptors, LBP has emerged as one of the most prominent and has attracted increasing attention in the field of image processing and computer vision due to its outstanding advantages: (1) ease of implementation, (2) no need for pre-training, (3) invariance to monotonic illumination changes, and (4) low computational complexity, making LBP a preferred choice for many applications. Although originally proposed for texture analysis, the LBP method has been successfully applied to many diverse areas of image processing: dynamic texture recognition, remote sensing, fingerprint matching, visual inspection, image retrieval, biomedical image analysis, face image analysis, motion analysis, edge detection, and environment modelling. Consequently many LBP variants are present in the recent literature.

DISADVANTAGES OF EXISTING SYSTEM:

Although significant progress has been made, most LBP variants still have prominent limitations, mostly the sensitivity to noise, and the limiting of LBP variants to three scales, failing to capture long range texture information.

- Although some efforts have been made to include complementary filtering techniques, these increase the computational complexity, running counter to the computational efficiency property of the LBP method.

II. RELATED WORK

The outline of the thesis is described below. Overview of Face Recognition: The structure of a generic face recognition is described. Firstly, the existing face recognition systems are categorised into holistic- and component-based methods. Secondly, the main baseline and state of art face recognition systems, configured from different processing modules are summarised. Some of the basic processing stages, including the geometric and photometric normalisation, the face representation, the feature selection and extraction, and the classifier are introduced. Ordinal measures for Face representation: Ordinal contrast encoding for face representation has recently become popular because the operation is simple and it captures the mutual ordinal relationships between neighbours at pixel level or region level, reflecting the intrinsic nature of the face.

III.PROPOSED WORK

In this paper, we propose a novel, computationally simple approach, the Rotation Invariant and Noise Tolerant descriptor, Motivated by the recent CLBP approach, which was proposed by Guo et al. to include both the signs and the magnitudes components between a given central pixel and its neighbors and the center pixel intensity in order to improve the discriminative power of the original LBP operator, we extend rotation invarient to include a magnitude component and to code the intensity of the center pixel. Based on these methods we develop a discriminative and robust combination for multi- resolution analysis, which will be demonstrated experimentally to perform robustly against changes in gray-scale, rotation, and noise without suffering any performance degradation under noise-free situations.

a. Advantages Of Proposed System

- It is highly discriminative, has low computational complexity, is highly robust to noise and rotation, and allows for compactly encoding a number of scales and arbitrarily large circular neighborhoods. At the feature extraction stage there is no pre-learning process and no additional parameters to be learned.

i. Local binary pattern

The original LBP method, proposed by Ojala *et al.* [11]in 1996, characterizes the spatial structure of a local image texture by thresholding a 3 X 3 square neighborhood with the value of the center pixel and considering only the sign information to form a local binary pattern. A more general formulation defined on circular symmetric neighborhood systems was proposed that allowed for multi-resolution analysis and rotation invariance. Formally, given a pixel *xc* in the image, the LBP pattern is computed by comparing itsvalue with those of its *p* neighboring pixels .The gray values of neighbors which do not fall exactly in the center of pixels are estimated by interpolation. Given an *N* X *M* texture image I, a LBP pattern *LBPr;p*(*i; j*) can be the computed at each pixel (*i; j*). A texture image can be characterized by the probability distribution of the LBP patterns. Formally, the whole textured image I is represented by a LBP histogram .To be able to include textural information at different scales, the LBP operator was later extended to use neighborhoods of different sizes [2], with values of (*r; p*) selected as (1*;* 8)*;* (2*;* 16)*;* (3*;* 24)*; : : : ;* (*r;* 8*r*).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 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's value, 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.

To date, the access to restricted systems has mostly been controlled by knowledge-based or token-based security, such as passwords and ID cards. However, such security control can easily fail when a password is divulged or a card is stolen. Furthermore, simple and short passwords are easy to guess by a fraudulent user, while long and complex passwords may be hard to memorise by a legitimate user. Therefore, the technologies of Biometric recognition are highly desired to address these problems. One of the biometric recognition modalities is face recognition which is non-intrusive, natural and easy to use.

ii. Radius

A consists of all points in a plane that are the same distance from a fixed point called the . The distance between the center and any point on the circle is the . The distance across the circle through the center is the . The of a circle is the distance around the circle. For any circle, the ratio of its circumference to its diameter is an irrational number that is approximately equal to 3.14 or 2 7 2 . The Greek letter π (pi) is used to represent this ratio. the **radius** of a circle or sphere is the length of a line segment from its centre to its perimeter.

The name comes from Latin *radius*, meaning "ray" but also the spoke of a chariot wheel.[1] The plural of *radius* can be either *radii* (from the Latin plural) or the conventional English plural *radiuses*.[2] The typical abbreviation and mathematic variable name for "radius" is **r**. By extension, the diameter **d** is defined as twice the radius:[3]

$$d = 2r \Rightarrow r = d/2$$

If an object does not have an obvious center, the term may refer to its **circum radius**, the radius of its circumscribed circle or circumscribed sphere. In either case, the radius may be more than half the diameter, which is usually defined as the maximum distance between any two points of the figure. The in radius of a geometric figure is usually the radius of the largest circle or sphere contained in it. The inner radius of a ring, tube or other hollow object is the radius of its cavity.

iii. Difference

A circle is a type of line. Imagine a straight line segment that is bent around until its ends join. Then arrange that loop until it is exactly circular - that is, all points along that line are the same distance from a center point.There is a difference between a circle and a disk. A circle is a line, and so, for example, has no area - just as a line has no area. A disk however is a round portion of a plane which has a circular outline. If you draw a circle on paper and cut it out, the round piece is a disk.

iv. Central pixel

The pixel (a word invented from "picture element") is the basic unit of programmable color on a computer display or in a computer image. Think of it as a logical - rather than a physical - unit. The physical size of a pixel depends on how you've set the resolution for the display screen. If you've set the display to its maximum resolution, the physical size of a pixel will equal the physical size of the dot pitch (let's just call it the dot size) of the display. If, however, you've set the resolution to something less than the maximum resolution, a pixel will be larger than the physical size of the screen's dot (that is, a pixel will use more than one dot). The specific color that a pixel describes is some blend of three components of the color spectrum - RGB. Up to three bytes of data are allocated for specifying a pixel's color, one byte for each major color component.

v. Absolute radius

The **radius of curvature**, *R*, of a curve at a point is a measure of the radius of the circular arc which best approximates the curve at that point. It is the inverse of the curvature. In the case of a space curve, the radius of curvature is the length of the curvature vector.

In the case of a plane curve, then *R* is the absolute value of

$$\frac{ds}{d\Phi} = \frac{1}{k}$$

where s is the arc length from a fixed point on the curve, φ is the tangential angle and κ is the curvature.

IV. EXPERIMENTAL JOINT HISTOGRAM

Joint entropy is finding in gray level image using joint histogram. Hill et al. [7] proposed an adaption of Woods' measure. They constructed a feature space(or joint histogram), which is a two dimensional plot showing the combinations of grey values in each of the two images for all corresponding points. The feature space is constructed by counting the number of times a combination of grey values occurs. For each pair of corresponding points (x, y), with x a point in the input image and y is a point in the reference image, the entry (input_image(x), Reference_image(y)) in the feature space on the right is increased. The feature space (or joint histogram) changes as the alignment of the images changes. When the images are correctly

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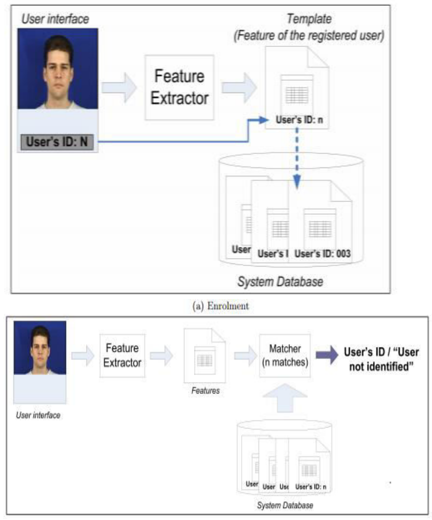
registered, corresponding anatomical structures overlap and the joint histogram will show certain clusters for the grey values of those structures.

A. *Support Vector Machine*

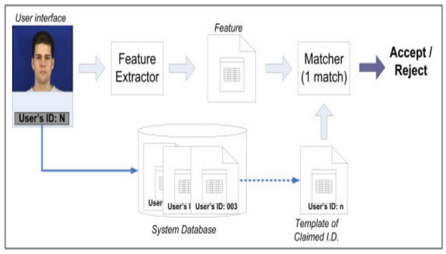
(SVM's) can generalize well on difficult image classification problems where the only features are high dimensional histograms. LARGE collections of images are becoming available to the public, from photo collections to Web pages or even video databases. To index or retrieve them is a challenge which is the focus of many research projects (for instance IBM's QBIC [1]). A large part of this research work is devoted to finding suitable representations for the images, and retrieval generally involves comparisons of images.SVMs introduced in COLT-92 by Boser, Guyon & Vapnik. Became rather popular since. • Theoretically well motivated algorithm: developed from Statistical Learning Theory (Vapnik & Chervonenkis) since the 60s. Empirically good performance: successful applications in many fields (bioinformatics, text, image recognition) Machine learning is about learning structure from data. • Although the class of algorithms called "SVM"s can do more, in this talk we focus on pattern recognition. • So we want to learn the mapping: X 7→ Y, where x ∈ X is some object and y ∈ Y is a class label. • Let's take the simplest case: 2-class classification. So: x ∈ Rn, y ∈ {±1}Face Recognition System A face recognition system can be either a verification system or an identification system depending on the context of an application. An identification system recognises a person by checking the entire template database for a match. It involves a one to many search. Block diagrams of the verification and identification systems respectively are presented in Figure . These systems consist of enrolment and matching. Enrolment is the first stage of face recognition. The objective of the enrolment is to register the person into the system database. In the enrolment phase, the image of a person is captured by a sensor to produce a raw digital representation.



(a) Enrolment

(b) Identification

Figure 1.1: Block diagrams of enrolment, identification and verification



(c) Verification

However, automated face recognition is not yet able to achieve comparable results because measuring the similarity between two faces is based on the conventional measures of image similarity, such as, Euclidean metric or Normalised correlation. As Euclidean metric measures the distance between the images, the smaller the distance the greater the similarity. On the other hand, Normalised correlation directly measures how similar two images are. It follows that these two measures are inverse to each other. Figure illustrates the inadequacy of these measures for assessing similarity in face recognition. Input image and LBP Image show the same person under even and uneven illumination, while Image 3 shows a different

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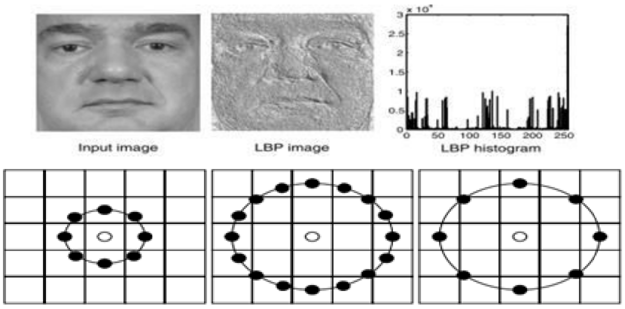
person. The template is a reference image belonging to the person in Image . Table clearly shows that similarity and distance measures would rate Image 3 to s be more similar to the template than Image 2. This simple test demonstrates that the similarity measurements fail to generalise in the presence of image degradation. Zhao et al. [6] and others[9] have discussed extensively the challenges of face recognition which raise issues in mathematics, computing, engineering, psychophysics and neuroscience. These challenges can be summarised in two points: (1) A large variability in facial appearance of the same person and (2) High dimensionality of data and small sample size. A large variability in facial appearance of the same person is caused by variations of facial pose, illumination, and facial expression. The most widely used versions of the operator are designed for monochrome still images but it has been extended also for color (multi channel) images as well as videos and volumetric data.



In contrast to the basic LBP using 8 pixels in a 3 × 3 pixel block, this generic formulation of the operator puts no limitations to the size of the neighborhood or to the number of sampling points. The derivation of the generic LBP presented below follows that of [2, 4, 5]. Consider a monochrome image I(x,y) and let gc denote the gray level of an arbitrary pixel (x,y), i.e. gc = I(x,y). Moreover, let gp denote the gray value of a sampling point in an evenly spaced circular neighborhood of P sampling points and radius R around point (x,y): gp = I(xp,yp), p = 0,...,P − 1 and (2.1) xp = x + R cos(2πp/P), (2.2) yp = y − R sin(2πp/P) for examples of local circular neighborhoods. Assuming that the local texture of the image I(x,y) is characterized by the joint distribution of gray values of P + 1 (P > 0) pixels: T = t(gc,g0,g1,...,gP−1). Without loss of information, the center pixel value can be subtracted from the neighborhood: T = t(gc,g0 − gc,g1 − gc,...,gP−1 − gc). In the next step the joint distribution is approximated by assuming the center pixel to be statistically independent of the differences, which allows for factorization of the distribution: T ≈ t(gc)t(g0 − gc,g1 − gc,...,gP−1 − gc). Now the first factor t(gc) is the intensity distribution over I(x,y). From the point of view of analyzing local textural patterns, it contains no useful information. Instead the joint distribution of differences t(g0 − gc,g1 − gc,...,gP−1 − gc) can be used to model the local texture. However, reliable estimation of this multidimensional distribution from image data can be difficult. One solution to this problem, proposed by Ojala et al. in [5], is to apply vector quantization. They used learning vector quantization with a codebook of 384 codewords to reduce the dimensionality of the high dimensional feature space. The indices of the 384 codewords correspond to the 384 bins in the histogram. Thus, this powerful operator based on signed gray-level differences can be regarded as a texton operator, resembling some more recent methods based on image patch exemplars (e.g. [3]).

The learning vector quantization based approach still has certain unfortunate properties that make its use difficult. First, the differences gp − gc are invariant to changes of the mean gray value of the image but not to other changes in gray levels. Second, in order to use it for texture classification the codebook must be trained similar to the other texton-based methods. In order to alleviate these challenges, only the signs of the differences are considered:

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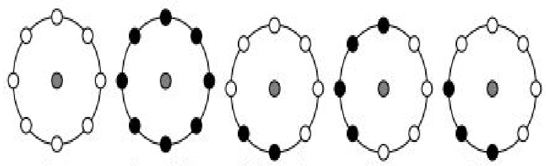
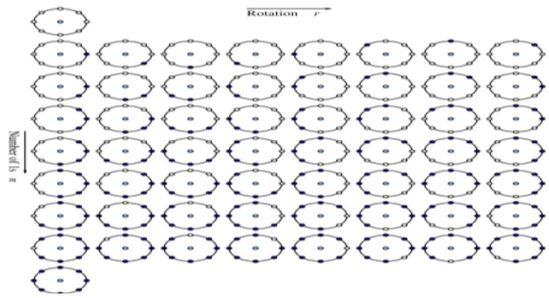
t(s(g0 − gc),s(g1 − gc),...,s(gP−1 − gc)), where s(z) is the thresholding (step) function s(z) = 1, z ≥ 0 0, z< 0. (2.9) The generic local binary pattern operator is derived from this joint distribution. As in the case of basic LBP, it is obtained by summing the thresholded difference weighted by powers of two. As the LBPP,R patterns are obtained by circularly sampling around the center pixel, rotation of the input image has two effects: each local neighborhood is rotated into other pixel location, and within each neighborhood, the sampling points on the circle surrounding the center point are rotated into a different orientation. Another extension to the original operator uses so called uniform patterns [5]. For this, a uniformity measure of a pattern is used: U ("pattern") is the number of bitwise transitions from 0 to 1 or vice versa when the bit pattern is considered circular. A local binary pattern is called uniform if its uniformity measure is at most 2. For example, the patterns 00000000 (0 transitions), 01110000 (2 transitions) and 11001111 (2 transitions) are uniform whereas the patterns 11001001 (4 transitions) and 01010011 (6 transitions) are not. In uniform LBP mapping there is a separate output label for each uniform pattern and all the non-uniform patterns are assigned to a single label. Thus, the number of different output labels for mapping for patterns



of P bits is P(P − 1) + 3. For instance, the uniform mapping produces 59 output labels for neighborhoods of 8 sampling points, and 243 labels for neighborhoods of 16 sampling points. The reasons for omitting the non-uniform patterns are twofold. First, most of the local binary patterns in natural images are uniform. Ojala et al. noticed that in their experiments with texture images, uniform patterns account for a bit less than 90% of all patterns when using the (8, 1) neighborhood and for around 70% in the (16, 2) neighborhood. In experiments with facial images [4] it was found that 90.6% of the patterns in the (8, 1) neighborhood and 85.2% of the patterns in the (8, 2) neighborhood are uniform. The second reason for considering uniform patterns is the statistical robustness. Using uniform patterns instead of all the possible patterns has produced better recognition results in many applications. On one hand, there are indications that uniform patterns themselves are more stable, i.e. less prone to noise and on the other hand, considering only uniform patterns makes the number of possible LBP labels significantly lower and reliable estimation of their distribution requires fewer samples. The combination of the structural and statistical approaches stems from the fact that the distribution of micro-textons can be seen as statistical placement rules. The LBP distribution therefore has both of the properties of a structural analysis method: texture primitives and placement rules. On the other hand, the distribution is just a statistic of a non-linearly filtered image, clearly making the method a statistical one. For these reasons, the LBP distribution can be successfully used in recognizing a wide variety of different textures, to which statistical and structural methods have normally been applied separately



Rotational Invariance Let UP (n,r) denote a specific uniform LBP pattern. The pair (n,r) specifies a uniform pattern so that n is the

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number of 1-bits in the pattern (corresponds to row number in Fig. 2.4) and r is the rotation of the pattern (column number in Fig. 2.4) [6]. Now if the neighborhood has P sampling points, n gets values from 0 to P + 1, where n = P + 1 is the special label marking all the non-uniform patterns. Furthermore, when 1 ≤ n ≤ P − 1, the rotation of the pattern is in the range 0 ≤ r ≤ P − 1. Let I α◦ (x,y) denote the rotation of image I(x,y) by α degrees. Under this rotation, point (x,y) is rotated to location (x ,y). A circular sampling neighborhood on points I(x,y) and I α◦ (x ,y) also rotates by α◦. See Fig. below [6].

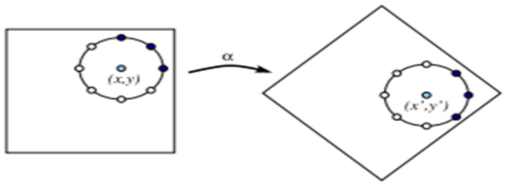

Fig: Effect of image rotation on points in circular neighborhood

If the rotations are limited to integer multiples of the angle between two sampling points, i.e. α = a 360◦ P ,a = 0, 1,...,P − 1, this rotates the sampling neighborhood by exactly a discrete steps. Therefore the uniform pattern UP (n,r) at point (x,y) is replaced by uniform pattern UP (n,r + a mod P) at point (x ,y) of the rotated image. From this observation, the original rotation invariant LBPs introduced in [3] and newer, histogram transformation based rotation invariant features described in [6] can be derived. These are discussed in the following

Computing the histogram of LBP codes normalizes for translation, and normalization for rotation is achieved by rotation invariant mapping. In this mapping, each LBP binary code is circularly rotated into its minimum value LBPri P,R = min i ROR(LBPP,R,i), where ROR(x,i) denotes the circular bitwise right rotation of bit sequence x by i steps. For instance, 8-bit LBP codes 10000010b, 00101000b, and 00000101b all map to the minimum code 00000101b. Omitting sampling artifacts, the histogram of LBPri P,R codes is invariant only to rotations of input image by angles a 360◦ P , a = 0, 1,...,P − 1. However classifi- cation experiments show that this descriptor is very robust to in-plane rotations of images by any angle. Rotation Invariance Using Histogram Transformations The rotation invariant LBP descriptor discussed above defined a mapping for individual LBP codes so that the histogram of the mapped codes is rotation invariant. In this section, a family of histogram transformations is presented that can be used to compute rotation invariant features from a uniform LBP histogram. Consider the uniform LBP histograms hI (UP (n,r)). The histogram value hI at bin UP (n,r) is the number of occurrences of uniform pattern UP (n,r) in image I . If the image I is rotated by α = a 360◦ P , this rotation of the input image causes a cyclic shift in the histogram along each of the rows, hI α◦ (UP (n,r + a)) = hI (UP (n,r)). For example, in the case of 8 neighbor LBP, when the input image is rotated by 45◦, the value from histogram bin U8(1, 0) = 000000001b moves to bin U8(1, 1) = 00000010b, the value from bin U8(1, 1) to bin U8(1, 2), etc. Therefore, to achieve invariance to rotations of input image, features computed along the input histogram rows and are invariant to cyclic shifts can be used. Discrete Fourier Transform is used to construct these features. Let H(n,·) be the DFT of nth row of the histogram hI (UP (n,r)), i.e. H(n,u) = P −1 r=0 hI (UP (n,r))e−i2πur/P . (2.15) In [6] it was shown that the Fourier magnitude spectrum |H(n,u)| = H(n,u)H(n,u) (2.16) of the histogram rows results in features that are invariant to rotations of the input image. Based on this property, an LBP-HF feature vector consisting of three LBP histogram values (all zeros, all ones, non-uniform) and Fourier magnitude spectrum values was defined. The feature vectors have the following form: fvLBP-HF = [|H(1, 0)|,...,|H(1,P/2)|, ..., |H(P − 1,

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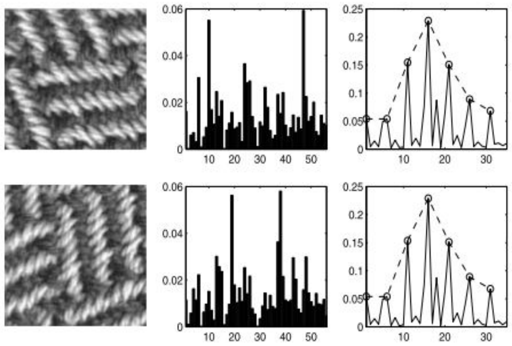
0)|,...,|H(P − 1,P/2)|, h(UP (0, 0)),h(UP (P, 0)),h(UP (P + 1, 0))]1×((P−1)(P/2+1)+3). It should also be noted that the Fourier magnitude spectrum contains rotationinvariant uniform pattern features LBPriu2 as a subset, since |H(n, 0)| = P −1 r=0 hI (UP (n,r)) = hLB Priu2 (n). An illustration of these features is in Fig. below [6].



Complementary Contrast Measure Contrast is a property of texture usually regarded as a very important cue for human vision, but the LBP operator by itself totally ignores the magnitude of gray level differences. In many applications, for example in industrial visual inspection, illumination can be accurately controlled. In such cases, a purely gray-scale invariant texture operator may waste useful information, and adding gray-scale dependent information may enhance the accuracy of the method. Furthermore, in applications such as image segmentation, gradual changes in illumination may not require the use of a gray-scale invariant method [2, 5]. In a more general view, texture is distinguished not only by texture patterns but also the strength of the patterns. Texture can thus be regarded as a two-dimensional phenomenon characterized by two orthogonal properties: spatial structure (patterns) and contrast (the strength of the patterns). Pattern information is independent of the gray scale, whereas contrast is not. On the other hand, contrast is not affected by rotation, but patterns are, by default. These two measures supplement each other in a very useful way. The LBP operator was originally designed just for this purpose: to complement a gray-scale dependent measure of the "amount" of texture. In [5], the joint distribution of LBP codes and a local contrast measure (LBP/C, see Fig. above) is used as a texture descriptor.

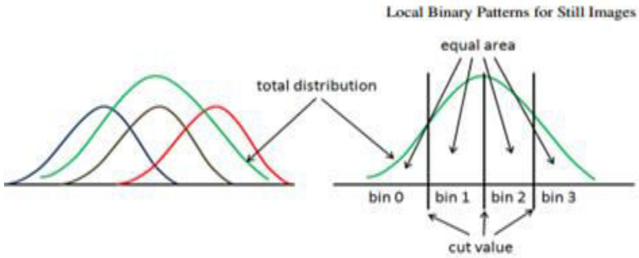


Fig: Quantization of feature space, when four bin are requested

Rotation invariant local contrast can be measured in a circularly symmetric neighbor set just like the LBP: VARP,R = 1 P P −1 p=0 (gp − μ)2, where μ = 1 P P −1 p=0 gp. VARP,R is, by definition, invariant against shifts in the gray scale. Since contrast is measured locally, the measure can resist even intra-image illumination variation as long as the absolute gray value differences are not much affected. A rotation invariant description of texture in terms of texture patterns and their strength is obtained with the joint distribution of LBP and local variance, denoted as LBPriu2 P1,R1 /VARP2,R2 . Typically, the neighborhood parameters are chosen so that P1 = P2 and R1 = R2, although nothing prevents one from choosing different values. Variance measure has a continuous-valued output; hence, quantization of its feature space is needed. In the experiments presented in this book, the value of B has been set so that this condition is satisfied. Above Figure illustrates quantization of the feature space, when four bins are requested. 7 Multiscale LBP A significant limitation of the original LBP operator is its small spatial support area. Features calculated in a local 3×3 neighborhood cannot capture large-scale structures that may be the dominant features of some textures. However, adjacent LBP codes

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are not totally independent of each other. Above Figure displays three adjacent four-bit LBP codes [4]. For example, a feature histogram obtained by concatenating histograms produced by rotation-invariant uniform pattern operators at three scales (1, 3 and 5) is denoted as: LBPriu2 8,1+16,3+24,5

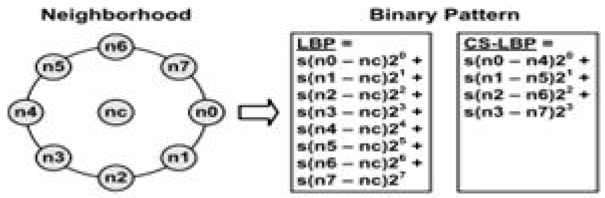

Fig: LBP and CS-LBP features for a neighborhood of 8 pixels

The aggregate sum of sample model can be calculated by

$$L_N=\sum_{n=1}^{n} L(s^n, M^n)$$

where S^n and M^n correspond to the sample and model distributions extracted by the nth operator [5, 3]. Even though the LBP codes at different radii are not statistically independent in the typical case, using multi-resolution analysis often enhances the discriminative power of the resulting features. This straightforward way of building a multi-scale LBP operator has resulted in very good accuracy. CSLBP was designed to have higher stability in flat image regions to increase the operator's robustness in flat areas, the differences are threshold at a typically non-zero threshold T . CS-LBP operator is thus defined as CS-LBPR,P,T (x,y) = (P/ 2)−1 p=0 s(gp − gp+(P/2) − T)2p, s(z) = 1 z ≥ 0 0 otherwise, where ni and ni+(N/2) correspond to the gray values of center-symmetric pairs of pixels of N equally spaced pixels on a circle of radius R. It should be noticed that the CS-LBP is closely related to gradient operator, because like some gradient operators it considers gray level differences between pairs of opposite pixels in a neighborhood.

V. Conclusion and Future Work

The simulation success of LBP techniques in diverse laptop imaginative and prescient issues and packages has inspired plenty new research on extraordinary editions. Due to its flexibility the LBP technique may be without difficulty modified to make it appropriate for the needs of different varieties of issues. The simple LBP has also some problems that need to be addressed. Therefore, several extensions and modifications of LBP had been proposed with an purpose to boom its robustness and discriminative strength. The choice of a right method for a given software depends on many factors, which include the discriminative strength, computational efficiency, robustness to illumination and other versions, and the imaging device used. Therefore the LBP (and LBP with assessment) operators offered inside the previous sections will typically offer a very good starting point while searching for the ideal variant for a given application.

VI. References.

1. X. Xie, M. Mirmehdi, A galaxy of texture features. In: M. Mirmehdi, X. Xie,J. Suri (eds.) Handbook of texture analysis, Imperial College Press (2008), pp.375–406.
2. T. Ojala, M. Pietik¨ainen, and T. M¨aenp¨a¨a, "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.
3. L. Liu, and P. Fieguth, "Texture classification from random features," *IEEE Trans.Pattern Anal. Mach. Intel.*, vol. 34, no. 3, pp. 574-586, March 2012.
4. J. Zhang, M. Marszalek, S. Lazebnik and C. Schmid, "Local features and kernels

for classification of texture and object categories: a comprehensive study," *Int. J.Comput. Vision*, vol. 73, no. 2, pp. 213-238, 2007.
5. M. Varma and A. Zisserman, "A statistical approach to texture classification from single images," *Int. J. Comput. Vision*, vol. 62, no. 1-2, pp. 61–81, 2005.
6. M. Varma and A. Zisserman, "A statistical approach to material classification using image patches," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 31, no. 11, pp. 2032-2047, Nov. 2009.
7. M. Crosier and L. D. Griffin, "Using basic image features for texture classification," *Int. J. Comput. Vision*, vol. 88, pp. 447–460, 2010.
8. B.S. Manjunathi, and W.Y. Ma, Texture Features for Browsing and Retrieval of Image Data, *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 18, no. 8, pp. 837–842, 1996.
9. L. Liu, B. Yang, P. Fieguth, Z. Yang and Y. Wei, "BRINT: A binary rotation invariant and noise tolerant texture descriptor," in IEEE International Conference on Image Processing (ICIP), pp. 255–259, 2013.