IMAGE FORGERY DETECTION FOR CONTENTS PRESERVATION BASED ON LOCAL TEXTURE DESCRIPTORS

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***Abstract*— This paper presents an automatic image forgery detection system based on local texture analysis in the application of image authentication. The classification system proposes the local texture descriptors such as DRLBP, DRLTP and RILPQ and with Euclidean distance classifier. These descriptors are used to extract the local finger print pattern in terms of features. It is used to differentiate the fake biometric from original one. DRLTP based histogram features are used to differentiate the local object in terms of contrast, shape and illumination changes. DRLBP is used to discriminate the local edge texture of fingerprint invariant to changes of contrast and shape. LPQ is based on the blur invariance property of the Fourier phase spectrum which uses the local phase information. Euclidean distance based features matching is used here to take decision (Original or forgery) based on the texture analysis. Finally the system performance will be measured using metrics such as sensitivity, specificity and accuracy.**

Index Terms—Forgery detection, DRLDP-LTP, RILPQ Descriptors, Distance Measurement

I. INTRODUCTION

From time to time images have been generally accepted as evidence of events of the depicted happenings. Because of dominance of computer in field of education, business and other field, acceptance of digital image as authorized document has become frequent .The ease of use and accessibility of software tools. [1] and low-cost hardware, makes it very simple to forge digital images leaving almost no trace of being subjected to any tampering . As such we cannot take the authenticity and integrity of digital images for granted [2]. This challenges the reliability of digital images offered as medical diagnosis, as evidence in courts, as newspaper items or as legal documents because of difficulty in differentiating original and modified contents. Digital forensics field has developed significantly to combat the problem of image forgeries in many domains like legal services, medical images, forensics, intelligence and sports [3, 4]. Substantial amount of work is carried out in the field of image forgery detection. This is evident from figure 1 which shows the number of papers that addressed image forgery detection in IEEE and science direct over last 10 years. In this context this paper presents a review of blind/passive image forgery detection techniques and attempt is made to survey most recent literature available on the subject.

II. PRECEDING WORKS

A. Gabor Features

The outputs of a symmetric and an ant symmetric kernel filter in each image point can be combined in a single quantity that is called the Gabor energy. This feature is related to the model of a specific type of orientation selective neuron in the primary visual cortex called the complex cell [35] and is defined in the following way:

$$e_{\lambda,\Theta}(x,y) = \sqrt{r^2_{\lambda,\Theta,0}(x,y) + r^2_{\lambda,\Theta,-(1/2)\pi}(x,y)}$$

Where and are the responses of the linear symmetric and anti symmetric Gabor filters, respectively. The result is a new, nonlinear filter bank of 24 channels. The Gabor energy is closely related to the local power spectrum. The local power spectrum associated with a pixel in an image is defined as the squared modulus of the Fourier transform of the product of the image function and a window function that restricts the Fourier analysis to a neighborhood of the pixel of interest.

B. Local Binary Pattern

The concept of local binary pattern (LBP) was introduced for texture classification. This approach has many advantages. For example, the LBP texture features have the following characteristics: 1) They are robust against illumination changes; 2) they are very fast to compute; 3) they do not require many parameters to be set; 4) they are local features; 5) they are invariant with respect to monotonic grayscale transformations and scaling; and 6) they have performed very well in many computer vision image retrieval applications. The LBP method has proved to outperform many existing methods, including the linear discriminate analysis and the principal component analysis. In order to deal with textures at different scales, the LBP operator was later extended to use neighbourhoods of different sizes. Defining the local neighborhood as a set of sampling points evenly spaced on a circle centered at the pixel to be labelled allows any radius and number of sampling points. When a sampling point does not fall in the center of a pixel, bilinear interpolation was employed.

C. Principal Component Analysis

PCA is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to (i.e., uncorrelated with) the preceding components. Principal components are guaranteed to be independent only if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables.

III. PROCESS OVERVIEW

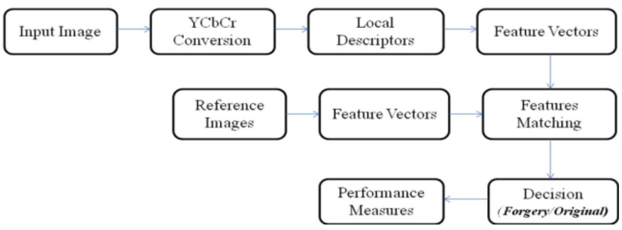

Fig 1 . Process overview

A. ROBUST LOCAL TEXTURE DESCRIPTORS

a) DRLBP/ LTP

Local Binary Pattern [11] operation is introduced by Ojale et al in1996. It summarizes local grey-level structure. The operator takes local neighborhood values around the pixel. It takes the central pixel and considers all the neighborhood values of central pixels. It is defined by 3X3 neighborhood where (2, 2) represents the central pixel. It is 8-bit coded based on central pixel. DRLBP operator takes,

$$DRLBP(x_c, y_c) = \sum_{n=0}^{7} 2^{n} s(i_n - i_c)$$

Here n has eight neighbours over central pixel c, where '***in***' and

'ic ' are grey scale values of c and n,

$$s(u) = \begin{cases} 1 & x \geq 0 \\ 0 & Otherwise \end{cases}$$

Here in DRLBP method we divide face image into a regular grid of cell. And histogram is applied for equalization. At last cell-level histogram concatenation produces uniform result. Here the threshold value is 70.And we will subtract the threshold values from the neighbouring pixels. And if the value is negative we will convert the value to 0.Otherwise if the value is positive we will convert it into 1.To obtain a small set of the most discriminative LBP-based features for better performance and dimensionality reduction, LBP-based representations are associated with some popular techniques of feature-selection schemes to reduce the feature length of DRLBP codes, which contain rule-based strategy, boosting and subspace learning, etc. A large number of variations are designed to expand the scope of application, which offer better performance as well improve the robustness in one or more aspects of the original DRLBP.

This histogram effectively has a description of the face on three different levels of locality: the DRLBP labels for the histogram contain information about the patterns on a pixel-level, the labels are summed over a small region to produce information on a regional level and the regional histograms are concatenated to build a global description of the face .It should be noted that when using the histogram based methods the regions do not need to be rectangular. It can be circular or any other. Neither do they need to be of the same size or shape, nor have to cover the whole image. It is also possible to have partially overlapping regions. Using a circular neighbourhood and bilinear interpolating values at non-integer pixel coordinates allow any radius and number of pixels in the neighbourhood. The gray scale variance of the local neighbourhood can be used as the complementary contrast measure. In the following, the notation (P,R) will be used for pixel neighbourhoods which mean P sampling points on a circle of radius of R. Another extension to the original operator is the definition of so called *uniform patterns*, which can be used to reduce the length of the feature vector and implement a simple rotation-invariant descriptor. This extension was inspired by the fact that some binary patterns occur more commonly in texture images than others. A local binary pattern is called uniform if the binary pattern contains at most two bitwise transitions from 0 to 1 or vice versa when the bit pattern is traversed circularly. It summarizes local grey-level structure.

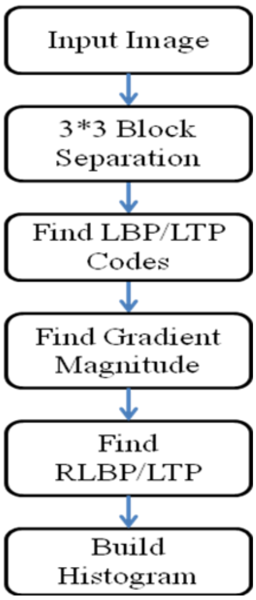

Fig2 . DRLBP/LTP Process Flow

RILPQ Descriptor

The rotation invariant local phase quantization (RILPQ) method is composed of two stages: characteristic orientation estimation and directed descriptor extraction. The Local Phase Quantization (LPQ) operator was originally proposed by Ojansivu and Heikkila as a texture descriptor. LPQ is based on the blur invariance property of the Fourier phase spectrum. It uses the local phase information extracted using the 2-D short-term Fourier transform (STFT) computed over a rectangular neighborhood at each pixel position of the image. These hybrid texture features extracted from samples are utilized for matching based on distance calculation. Finally the performance of these descriptors is measured with metrics such as sensitivity and accuracy.

Fig 3 . Detected result of the image

III. CONCLUSION

In this paper, an automatic image forgery detection system based on local texture analysis in the application of image authentication. The classification system proposes the local texture descriptors such as DRLBP, DRLTP and RILPQ and with Euclidean distance classifier. Finally the system performance will be measured using metrics such as sensitivity, specificity and accuracy.

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