Image Detection and Verification Using Local Binary Pattern with SVM

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Abstract: Local Binary Patterns (LBP) is a non-parametric descriptor whose aim is to efficiently summarize the local structures of images. In recent years, it has aroused increasing interest in many areas of image processing and computer vision, and has shown its effectiveness in a number of applications, in particular for facial image analysis, including tasks as diverse as face detection, face recognition, facial expression analysis, demographic classification, etc. This paper presents a comprehensive survey of LBP methodology including several more recent variations. As a typical application of the LBP approach, LBP-based facial image analysis is extensively reviewed, while its successful extensions in dealing with various tasks of facial image analysis are also highlighted.
Keywords - Image classification, local binary patterns, Support Vector Machine (SVM), Image Forensic

I.INTRODUCTION

Automatic image categorization based on visual content is an vital problem in computer vision. The goal of an image classification system is to assign a category with the most comparable visual content to the given input image. In general, there are two main steps of an image classification system. The first step is to define a robust and compact image description (feature) which includes sufficient information for the forthcoming classification step. Visual similarity between images is measured using extracted descriptors, where the choice of the descriptor essentially affects the overall performance of the classification system. As one of the most successful, Local Binary Pattern (LBP) descriptor has gain large popularity due to: robustness to resolution and lighting changes, low computational complexity, and compact

representation. In this work we will further improve its robustness by including color and multi-resolution information. Concretely we will extend LBP by extracting it over separate color channels and multiple image scales, what will lead to improved classification results. The second phase of the system is to predict the category of the input image using appropriate classifier. It is the crucial to choose an appropriate machine learning technique to be applied for classification of descriptors. Support Vector Machine (SVM) is the most widely used machine learning technique for image classification purposes. Despite its popularity it was found that SVM has to be combined with nonlinear kernels to achieve highly accurate results. However, nonlinear SVM introduces significant computational costs during training and testing steps, what makes this approach difficult to apply for real time applications.

Local Binary Patterns – LBP

LBP operator was introduced by Ojala in 1996 for texture classification, later it was used for face recognition , facial expression recognition and so on. In the early stage, the image is divided into several equal sized windows and represented as the combination of LBPH features from all windows; the classification methods can be nearest neighbors or linear programming. Later, the LBPH features with various sizes and locations are used as weak classifiers, from which JS Boosting is used to learn a strong face recognition classifier by Huang et al. In this paper, we use LBP histogram for demo graphic classification, which is age, gender and ethnicity classification, by face texture. Age is classified into three periods: child, youth and oldness; ethnicity is classified into Asian and non-Asian. We treat demographic classification as an ordinary binary classification problem, regarding age as a composition of two binary classifications. Our method is integrated with face detection to form an automatic system. Human face represents a variety of information, such as identity, age, gender, ethnicity, expression and so on. Specifically for one person, gender and ethnicity always remain the same as his or her identity does, while his or her age changes. As a result, it is reasonable that age classification is even harder. Recent works on demographic classification can be divided into two main approaches. One is pattern classification by face texture, such as decision tree , SVM ,

Local Binary Pattern (LBP) is a popular visual descriptor that captures local appearance around a pixel. LBP descriptor of the complete image is then formed as a histogram of quantized LBP values computed for every pixel of the image. It was introduced in for the texture classification problem, and extended to general neighborhood sizes and rotation invariance in . Since then, LBP has been extended and applied to variety of applications. For a given image I, the local LBP descriptor centered at pixel $I(x,y)$ is an array of 8 bits, with one bit encoding each of the pixels in the 3×3 neighborhood (Figure 1). Each neighbor bit is set to 0 or 1, depending on whether the intensity of the corresponding pixel is greater than the intensity of the central pixel. To form a binary array, neighbors are scanned in anti-clockwise order, starting from the one to the right at position $I(x+1,y)$.

178	230	229
129	**215**	197
212	250	212

a)

0	1	1
0		0
0	1	0

b)

01100010

c)

Fig. 1. Example of a LBP extraction process for the central pixel of intensity 215: a) pixel intensities, b)
Threshold difference, c) LBP.

II.RELATED WORK

The literature surveys that containing study of different features of images like aliasing blurriness, color contrast etc also different image classification techniques such as SVM, LBP Linear SVM etc

A. Features Of Recaptured Images

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In this section we provide an overview of some of the more common features found in images that have been recaptured from LCD monitors.

1 Aliasing:

Aliasing is sometimes introduced in digital camera images when the scene is insufficiently band-limited or contains detail with very high spatial frequencies. In cameras that are equipped with a Color Filter Array (CFA)the color channels are normally sampled at frequencies that are lower than the native frequency of the image sensor The recapture of an image displayed on the screen of an LCD monitor is, therefore, highly likely to introduce aliasing due to the high frequency periodic pattern of the monitor pixel grid structure. Indeed, casually recaptured still images or videos of LCDs are often characterized by the presence of aliasing artifacts, also referred to as color moiré, over the visible region of the display.

2 Blurriness:

There are three possible scenarios that blurriness can arise in a recaptured image. First, the first capture device or the printing device could be of low resolution. Second, the attack image may be small and the display medium may have to be placed outside of the focus range due to a specific recaptured setting. One way of characterizing the blur is with the point spread function (PSF) of the capture device. In practice measuring the PSF of a device is not easily achieved and the line spread function (LSF) is used instead.

B. Methodology

An Investigation into Aliasing In Images Recaptured From An LCD Monitor Using A Digital Camera:

Hani Muammar and Pier Luigi Dragotti investigated one approach to detecting an image that has been recaptured from an LCD monitor is to search for the presence of aliasing due to the sampling of the monitor pixel grid. An analysis of aliasing in recaptured images of LCD monitors using digital cameras equipped with a Bayer CFA was presented. The periodic structure of the monitor pixel grid projected on the camera's image sensor was modeled in one dimension by a 2-dimensional square wave. In this paper they show that aliasing can be completely eliminated in a recaptured image by setting the camera to monitor distance to a value determined by the camera lens focal length, the pixel pitch of the LCD monitor and the pixel pitch of the camera's image sensor. A recapture detector should not therefore rely solely on the presence of aliasing, but should make use of other features present in recaptured images such as high scene tonal contrast, changes in color balance and loss in perceived sharpness.

Advantages:

- Very effective technique to eliminate aliasing effect from recaptured images.

Disadvantages:

- Paper investigation is in aliasing only.
- Camera dependency.
- User should have knowledge about technical details of captures of camera.

An Image Recapture Detection Algorithm Based on Learning Dictionaries of Edge Profiles:

Thirapiroon Thongkamwitoon, Hani Muammar, and Pier-Luigi Dragotti proposed algorithm to detect recapture image based on learning dictionaries of edge profiles. They proposed a method for image recapture detection based on the blurriness of edges.

Robust Image Recapture Detection Using K-SVD Learning Approach To Train Dictionaries Of Edge Profiles:

Thirapiroon Thongkamwitoon, Hani Muammar, and Pier Luigi Dragotti show that it is possible to detect a recaptured image from the unique nature of the edge profiles present in the image. They leverage the fact that the edge profiles of single and recaptured images are markedly different and they train two alternative dictionaries using the KSVD approach. One dictionary is trained to provide a sparse representation of single captured edges and a second for recaptured edges. Using these two learned dictionaries, they can determine whether a query image has been recaptured. They achieve this by observing the type of dictionary that gives the smallest error in a sparse representation of the edges of the query image.

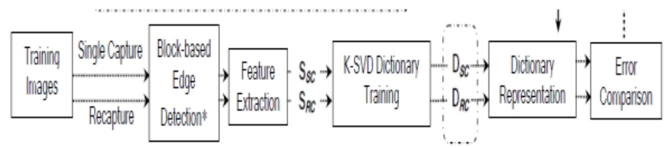

Fig Flow of Recapture detection

III. PROPOSED SYSTEM

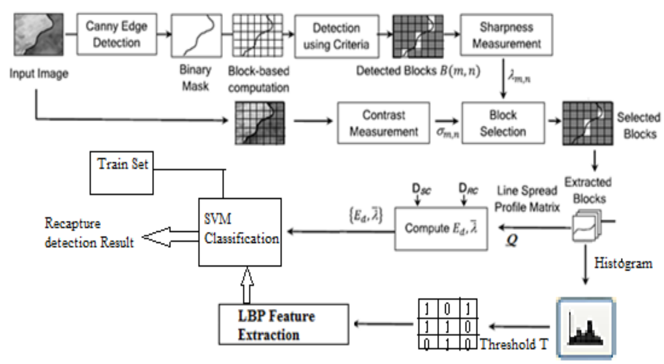

Fig. . General Flow of Proposed System

1. *Solving approach*

A method that uses the edge blurriness and distortion introduced by the recapture process as a feature to detect if a given image has been recaptured from an LCD monitor. We show that the edges found in single and recaptured images can be fully characterized by their line spread function (LSF). We then describe how sets of elementary atoms that provide a sparse representation of LSFs can be learned using the K-SVD dictionary learning method. Specifically, a single-capture dictionary is created from a training set of single captured images and a second one from recaptured images. We also compute an edge spread width from the line spread function of the image and combine this feature with the dictionary approximation errors to train an SVM classifier. We classify a query image as single or recaptured depending on its location relative to the SVM hyper plane.

a) Learning Dictionaries:

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The objective of dictionary learning is to obtain two over complete dictionaries, DSC and DRC, that provide an optimal sparse representation of line spread profiles from single captured and recaptured images, respectively. Dictionary training can be used as a tool to learn the characteristics of the distortion patterns present in edges found in most naturally occurring images. The key insight being that the descriptions in single capture and recaptured images are fundamentally different due to the sharpness degradation introduced by the recapture process.

The first step in dictionary training is to determine the training feature matrices, SSC and SRC, for single captured and recaptured images, respectively. For each set of training images, ISC and IRC, the set of line spread profiles, QjSC and QjRC, is constructed using the method described in Section IV-B. The superscript, j, denotes the individual images contained in each training set. The training feature matrices, SSC and SRC, are determined by concatenating horizontally the extracted line spread profiles matrices, QjSC and QjRC, over all the training images in each respective set. Thus, the resulting training feature matrix, S ∈ IRW×Contains N training line spread profiles qi ∈ IRW,

where= 1, 2, ・・・, N, and N _ W.

Given the training feature matrix S, the goal of dictionary training is to obtain the best dictionary, D ∈ IRW×K, that provides an optimal sparse representation for all the line spread profiles in the training matrix S, that is

Where X ∈ IRK×N is built from the column vectors xi used to represent the feature qi and i= 1, 2. . . N. The notation_A_2F refers to the Frobenius norm, which is defined as_A_2F= _ij|Ai j |2. The constant L is the maximum number of atoms permitted. The choice of L is generally a tradeoff between approximation precision and sparsely. Our dictionary is designed using the K-SVD learning approach [19]. The K-SVD method is an iterative learning scheme based on two important steps for each round of computation: sparse coding and dictionary update. In sparse coding, given an initial dictionary D, X is chosen such that each of its columns xi provides the best L-sparse representation of qi .

Specifically: $$\min_{x_i} \|\mathbf{q}_i - \mathbf{D}\mathbf{x}_i\|_2^2 \quad \text{subject to } \|\mathbf{x}_i\|_0 \le L$$

In K-SVD, the dictionary atoms are updated, one column at a time, at the kth column index, where k = 1, 2, . . . , K. The residual error in (14) is computed using only the training profiles that use the kth atom for approximation. Next, the atom which minimizes the residual error can be obtained using singular value decomposition (SVD) approach. We replace the kth column with this new atom. The process is then repeated for all K columns. Given the new D, a new X is found by sparse coding and the process is repeated. As a result, the training error is reduced over several iterations and the dictionary D has been trained to fit all training profile sin S.

By training two dictionaries, DSC and DRC, using the training feature matrices SSC and SRC, we ensure that the patterns from line spread profiles extracted from single captured and recaptured images will have been learned. Each dictionary provides an optimal sparse representation of the line spread features from each class of image.

B. Algorithmic Approach:

Module 1:

1. Get Query Image Q
2. Convert Image Q to grayscale Qq
3. The query image Q is divided into a number of non-overlapping square blocks B(m, n) of size W × W with W = 16 pixels. Here m and n are the vertical and horizontal indices of the block respectively.
4. Canny Edge Detection Algorithm:
5. The Process of Canny edge detection algorithm can be broken down to 5 different steps:

a. Apply Gaussian filter to smooth the image in order to remove the noise

Find the intensity gradients of the image

b. Apply non-maximum suppression to get rid of spurious response to edge detection

c. Apply double threshold to determine potential edges

d. Track edge by hysteresis: Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges.

Module 2:

1. Check for sharp edge

For each Block {B0……..Bn}

Check horizontal or near horizontal sharp single edge

Rotate block by 90 degree

Check for vertical sharp edge

2. Block Selection

Block Bi is detected when

Ɗ ≥ βW

Where Ɗ= No. of columns, β= 0.6

3. The detected blocks, B(m, n) are then ranked according to their sharpness and edge contrast.

4. Calculate line profile matrix Q, λ, Ed.

a. Compute spectral Energy eqi

b. When w=1

Compute spectral Energy ew

c. Compute ratio ew/eqi

If (ew/eqi)> 0.95

Then λ=w else

Goto b

d. $E_d = E_{sc} - E_{RC}$

$$\|\mathbf{Q} - \mathbf{D}_{SC}\mathbf{X}_1\|_F^2 - \|\mathbf{Q} - \mathbf{D}_{RC}\mathbf{X}_2\|_F^2,$$

where X1 is the corresponding coefficients matrix computed using the orthogonal matching pursuit algorithm with the dictionary DSC.

B .Mathematical Model

Two sets of known images,

ISC={Isc0, Isc1,…………Iscn} set of single captured images

IRC={Irc0, Irc1,…………Ircn} set of recaptured images

1. Set of edge profiles for each image

I ={E1, E2,………….En}

2. Set of line spread profiles for each image

={q0, q1,………qi}

3. A matrix Qsc for Isc and Qrc for Irc

$q0$ .. ..

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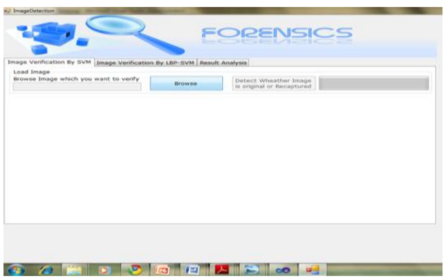
.. .. ..
.. .. qi

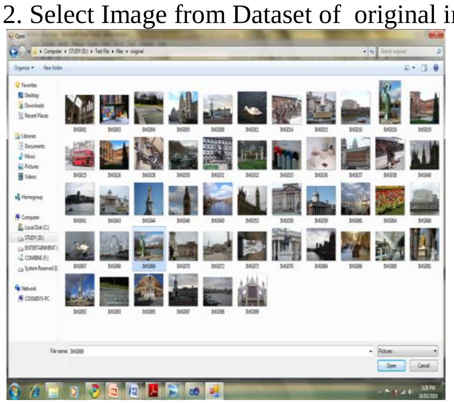
4. A dictionary Dsc and Drc
Dsc={Isc0,………Iscn}
Drc={Irc0,………Ircn}
Dictionary is optimal sparse representation of q
5. Sparse Representation include {λ, Ed}
Λ= average line spread width
Ed= sparse representation of error
Ed={Esc- Erc}
6. SVM Training
Isc={training set of images of single capture}
Irc={training set of images of recapture}

C.Implementation Details:

Image Classification detection system is implemented on Windows 7 system with Intel i7 5th Gen @ 2.4GHz and 2GB RAM using .Net Framework 4.5 in C#.
It is developed for two types i.e for original images and recaptured images.
1. Browse an Image



2. Select Image from Dataset of original images



3. Results of image

4. Results of image

IV.PERFORMANCE EVALUATION

The test results show that the average success rate for observers in classifying the images was only 63.63%. This level of precision is fairly close to the accuracy that would be obtained in a random choice, binary classification experiment. In addition, the results suggest that observers have a greater tendency to classify recaptured images as originally captured. This is highlighted by the differences in success rates between originally captured images (69.81%) and recaptured images (57.45%). Most importantly, it supports our claim that to detect recaptured images in our dataset by visual inspection is a difficult task.

Technique			**Subjective Classification statistics**		
	Image Type	**No. Of Images**	**Original Captured**	**Recaptured**	**Success Rate (%)**
Base Paper Technique	Original Captured	50	33.87	16.13	67.75
	Recaptured	50	22.57	27.43	54.86
	Overall	100			61.31
Proposed Technique	Original Captured	50	35.23	18.12	69.81
	Recaptured	50	25.89	29.56	57.45
	Overall	100			63.63

Table: Comparison of Existing and Proposed work

2. The Comparison of Performance of Different Algorithms

Following table describes the classification of different algorithms which have been used for the image classification. The success rate is calculated for both original and recaptured images.

Method	Number of Features	Success Rate (%)	
		Original Captured	Recaptured
MSWS+LBP+Colour Features [8]	129	83.67	92.02
Higher-order Wavelet Statistics [41]	216	87.56	90.04
Proposed Method	4	94.89	99.03

Table: The comparison of the different algorithms

Now as we know the accuracy for the image classification can be calculated with different parameters , in our system we are mainly using the parameters to calculate the accuracy is “Precision and Recall”. Following graph shows the diagrammatic representation of the accuracy.

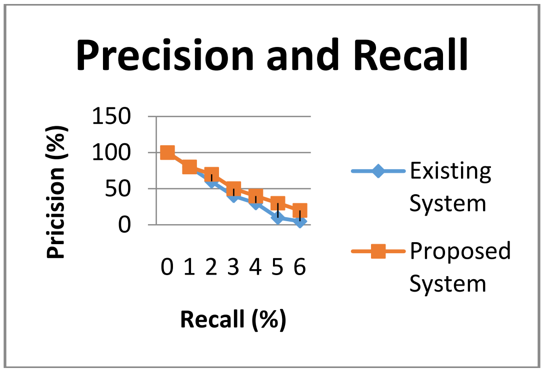


Figure : Graph showing precision and recall.

V.Conclusion

This paper, help to study various features which can distinguish original images from recaptured one like aliasing, blurriness, noise, surface gradient etc. Using these features several researchers proposed new algorithms to detect recaptured images or videos. So here we study algorithms of many researchers who used different features for detection of recapture image.

As future work, it will be interesting to analyze more feature of image which can be useful for classification. Also no author works on 3D- images, so this is another interesting direction to proceed this work on 3D images. As per previous work for classification of images many authors used SVM algorithm, so it will another direction for researcher to do more analysis on another machine learning algorithms for better result.

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