International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 5, May - 2014

Robust Image Forgery Localization for JPEG Artifacts

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***Abstract*—Images are powerful tool for communication and application purpose. Image manipulation is done by splicing techniques for harmless manipulation cases. So identification of true photographs like evidences for real world events. To detect and localize the tampered area into a digital image for forgery purpose new algorithms are used. It is based on machine learning approach and less number of user's interaction is required. This technique is applicable to image containing information with respect to no expert interaction for the tampering decision. Statistical based illuminant estimator to extract the texture and edge based features these features are then provided to a machine learning approach for automatic decision making. This Image forgery detection method based on SIFT.A part of an image is taken from one image and they are pasted on a different location in the different image, from that we are finding the forged image. In this approach an improved algorithm based on scale invariant features transform (SIFT) is used to detect such forgery, In this technique Transform is applied to the input image to yield a reduced dimensional representation, After that Apply key point detection and feature descriptor along with a matching over all the key points matching. Furthermore gives output by applying matched points. Although photographers are able to create composites of analog pictures, this process is very time consuming. One of the most common forms of photographic manipulation is known as image composition or splicing.**

Keywords*— *Illuminant; SIFT; tampering; machine learning; texture and edge based; Splicing.

I. INTRODUCTION

Digital image processing is a subset which belongs to the electronic domain. In this the image is changed in to an array of small integers, called pixels, which says about the physical quantity that is scene radiance, which is processed by digital hardware and stored in the digital memory. Digital image processing either in the field of improving in human perception or observing their performance leads to the advantage in cost, speed and adaptability. Nowadays it has become the dominant method to be used in all the fields like medical, biometrics, forgery etc. The image that is captured by the digital camera is used to identify where the particular person face is located and where the person is present in the picture. In this system we have considered face as a biometric to detect the forgery for the following reasons.

- The procurement process is non intrusive
- The procurement process of a face is cheaper simpler and accurate compared to other biometrics such as iris and fingerprints.
- This technique is secured

There are many steps in face detection methods, first it finds out whether the given input image is human image and checks where the image is present in the database. In the second step, the patches in each face are detected and the output from this step is given to the face extraction phase. In this phase, the face which is in the database will be extracted separately. In order to justify the orientation of the patches we need a robustness to design the system feasibly. Normally, face detection methods focuses mainly on the shape and colour of the face and not on the other features in the face.

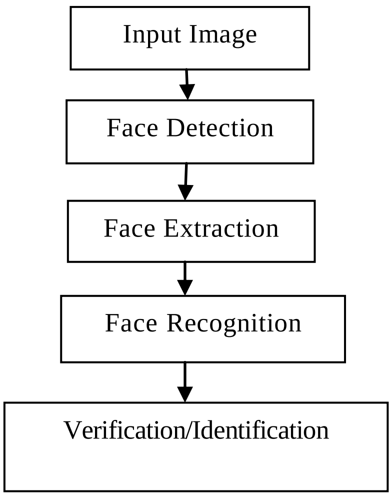

Fig.1. Flow diagram of face recognition

In face recognition, the patches in the face may have some drawbacks stated below:

- Usually, the size of the patches is of more than 1000 pixels, which leads to a non-robustness recognition system.
- Occlusion and clutter problem arises in the face patch due to different camera alignments, illuminations and face expressions.

After the feature extraction step, the face patches are dimensionally converted in to vectors fiducially based on their locations.

The feature extraction is followed by face Recognition phase where the identities of each face is recognised. If the face database is present, then the automatic recognition is achieved. The two different applications such as face identification and face verification are explained below.

Face identification checks whether the given face image is present in the database among the known individuals that works under one-to- many relationship.

Face Verification verifies whether the unknown individual's identity matches with the database. This performs one-to-one relationship.

II. RELATED WORKS

J. F. O'Brien [7] et al proposed that a new forensic technique that focuses on geometric inconsistencies that arise when fake reflections are inserted into a photograph or when a photograph containing reflections is manipulated. This analysis employs basic rules of reflective geometry and linear perspective projection, makes minimal assumptions about the scene geometry, and only requires the user to identify corresponding points on an object and its reflection. The analysis is also insensitive to common image editing operations such as resampling, color manipulations, and lossy compression. Images are highly blurry or distorted, highly overlapping occurs by this technique

Y. Ostrovsky [18] et al report an unexpected failure of this ability in the context of perceiving inconsistencies removed, the visual system is remarkably insensitive to illumination inconsistencies, both in experimental stimuli and in altered images of real scenes. Whether the target is interpreted as oddly illuminated or oddly pigmented, it is very difficult to find if the only cue is deviation from the regularity of illumination or reflectance. Our results allow us to draw inferences about how the visual system encodes illumination distributions across scenes. Specifically, they suggest that the visual system does not verify the global consistency of locally derived estimates of illumination direction. Noise is high; direction of illumination is slow to compute are the major flaws.

S. Gholap et al [11] proposed a physics-based approach for illuminant color estimation of arbitrary images, which is explicitly designed for handling images with multiple illuminants. The majority of techniques that extract the illuminant color assume that the illumination is constant across the scene. We propose an illuminant-color estimation method which is based on robust local illuminant estimates. An illuminant color estimate is obtained independently from distinct image mini-regions. From these mini-regions a robust local illumination color is computed by consensus. These local estimates are then used in deriving the chromaticity of the dominant illuminants. Furthermore, extensive tests on real-world images show that we can reliably process mixed illuminant. Uniform illumination can not accurately recover the illuminant are the major flaws reported.

M. Johnson et al [3] the availability of sophisticated digital imaging technology has given rise to digital forgeries that are increasing in sophistication and frequency. We describe a technique for exposing such fakes by detecting inconsistencies in lighting. We show how to approximate complex lighting environments with a low-dimensional model and, further, how to estimate the model's parameters from a single image. Inconsistencies in the lighting model are then used as evidence of tampering. More accurate results, High dynamic range images are produced.

C. Riess [24] et al presents a physics-based approach for illuminant color estimation of arbitrary images, which is explicitly designed for handling images with multiple illuminants. The majority of techniques that extract the illuminant color assume that the illumination is constant across the scene. This, however, is not often the case. We propose an illuminant-color estimation method which is based on robust local illuminant estimates. There are no assumptions on the number or type of illuminants. An illuminant color estimate is obtained independently from distinct image mini-regions. From these mini-regions a robust local illumination color is computed by consensus. These local estimates are then used in deriving the chromaticity of the dominant illuminants. Experiments on an established benchmark database of real-world images show that our technique performs comparably to uniform-illuminant estimation methods. Furthermore, extensive tests on real-world images show that we can reliably process mixed illuminant. Uniform illumination can not accurately recover the illuminant.

III. FORGERY DETECTION FRAMEWORK

A. Overview

This project deals with forgery detection. There are different types of forgeries are there, they are mainly used for forgery purpose in courts etc. They are done in faces, signatures, voices etc. In this the persons who are add to original image is detected and say that the image is the forged one. This is calculated by help of SIFT and key point matching. The color image is being used as input for forgery purpose. Several steps are used.

B. System Module Description

Face detection:

In this step from the input image Fig 2.a the noise that are present in the image are being filtered by help of IM filters and produces smooth image or fabric image Fig2.b.From the fabric image it is converted to RGB layers Fig 2.c, Fig2.d, Fig2.e then it is converted to YCbCr image Fig2.f because RGB image is difficult to convert the image for further process that is the pixel value is more, so we are converting to YCbCr image. The YCbCr image is converted to gray image Fig 2.g.Then the segmentation map is done for the image Fig 2.h.

SIFT features (Scale-invariant feature transform):

SIFT method, is used to determine the key points, for the entire image by key point detection and feature descriptor. This approach is known as the Scale Invariant Feature Transform (SIFT), related to local features the image data is transformed to scale-invariant coordinates. By converting RGB image to gray scale image Fig 2.g the key point value is calculated.

Append Images:

Append is for adding of two or more image with the original image. The image that is being added to the original image will of same pixels and same values. Only joining is done in this step.

Key point matching:

Key point is the method, used for matching extracted feature from the image by SIFT algorithm. This reads the input image key point and forged image points and then, it compares the key point image and draws the line indicating the matched points. Then append the two images and draw a line which indicates the matches' Fig 2.j.

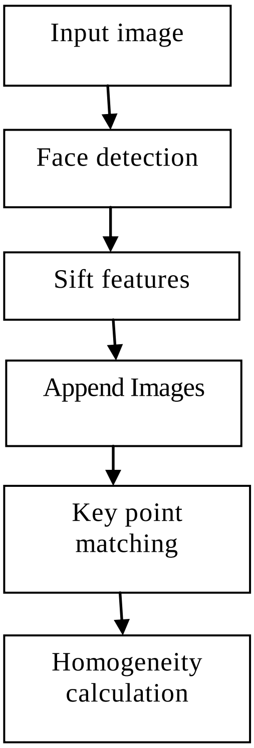

Fig.2. Flow chart diagram for forgery detection

Homogeneity Calculation:

It says the relationship between the original image and forged image by help of key points. The transformation matrix are calculated by help of correspondent points .The input image that is added again with the forged image will have the same value but other persons who are added with the image will have the different value, from that it is said to be the forged image Fig 2.k the and the output comes as forgery is detected.

IV. RESULTS AND DISCUSSION

The image produced is of high quality when compared with forensic algorithm, because the image produced was blur image to avoid that, we used different method. This will increase the overall performance and computation of the system during result execution. Analysis is based on accuracy of image which is compared with forensic the algorithm SIFT, RANSAC gives better result is given below.

Fig. 2.a. Input image

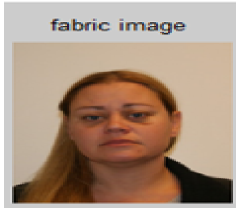

Fig. 2.b.Fabric image

Fig. 2.c.Red image

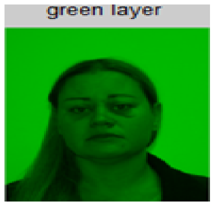

Fig. 2.d. Green image

Fig. 2.e. Blue image

Fig. 2.f. YCbCr image

Fig. 2.g. Gray image

Fig. 2.h. Segmentation map

Fig. 2.i.Altered image

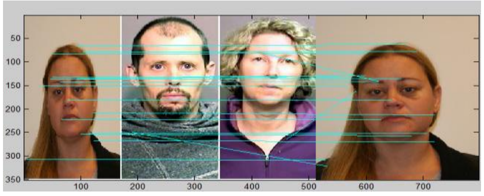

Fig. 2.j. key point matching

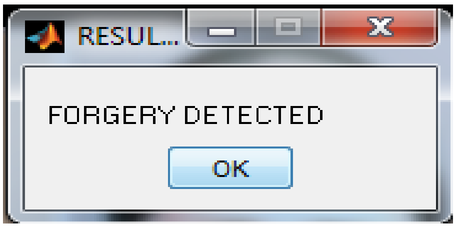

Fig. 2.k. Result

V. CONCLUSION

In this work, we presented a new method for detecting forged image by using SIFT and RANSAC algorithm this effectively detects the forged image that is being added with the original image. We can produce better quality image than this by help of Surf algorithm in the future.

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