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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.

2.3Contrast, Color and Illumination Non-Uniformity

Because the light transmitted from the back can significantly reduce the contrast and saturation of a recaptured image, the color of finely recaptured images still looks different from their original images. Contrast and color moments for an image can be computed as a distinguishing feature. Color balance errors in a recaptured image can be minimized by calibrating the display monitor and by presetting the white point of the recapture camera to the LCD monitor white point before recapture.

A luminance gradient may be noticeable in recaptured images containing large regions that are low in texture or detail. Identification of the luminance gradient would enable recaptured images to be detected.

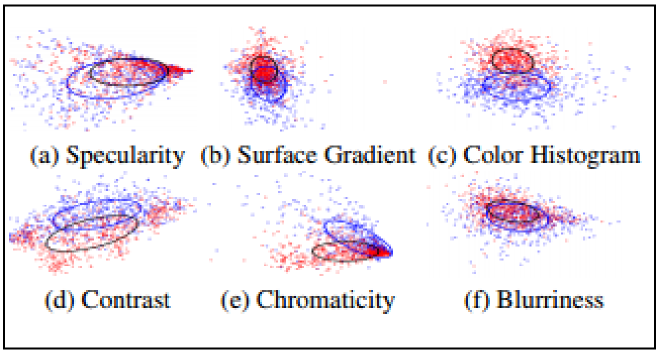

Figure 2: 2D projection of the physical feature distribution for the real-scene image sets (red) and the recaptured image sets (blue).

3. Existing System

3.1 An Investigation into Aliasing In Images Recaptured From An LCD Monitor Using A Digital Camera [2]:

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 modelled 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.

3.2 An Image Recapture Detection Algorithm Based on Learning Dictionaries of Edge Profiles [1]:

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.

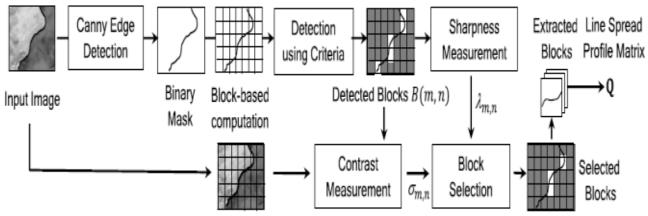

Figure 3: Working diagram of the automatic block-based edge detection algorithm.

Algorithm 1:

Step 1: Firstly, the query image is converted to greyscale.
Step 2: all edges contained in the image are detected using a Canny Edge Detector.
Step 3: Edge profiles are extracted locally
The query image 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.
Step 4: For each block, first check whether it contains a horizontal or near horizontal sharp single edge.
Step 5: The block will be detected only when the condition $\eta \geq \beta W, \beta=0.6$
Step 6: The detected blocks, B (m, n), are then ranked according to their sharpness and edge contrast.
Block sharpness is determined using the technique in which the average width $\bar{\lambda}_{m,n}$ of line spread profiles of the Blocks are estimated.
The contrast of a block is measured by computing the block-based variance, $\sigma_{m,n}$, of the input image at the detected block.333
Step 7: Create Feature matrix:
let $Y \in \mathrm{IR}^{W \times W}$ be a matrix which represents the grey scale values of a block. Each column, y_i ; i = 1, 2, · · · ,W, of the matrix Y may, therefore, be considered to represent an edge profile of the image.
This feature matrix is used for training and testing purposes. Here authors used SVM classification algorithm for labeling to images.

Advantages:
- Very good success rate for dataset.

Disadvantages:
- Need to remove aliasing factor from image.
- Technique work for images only

3.3 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.

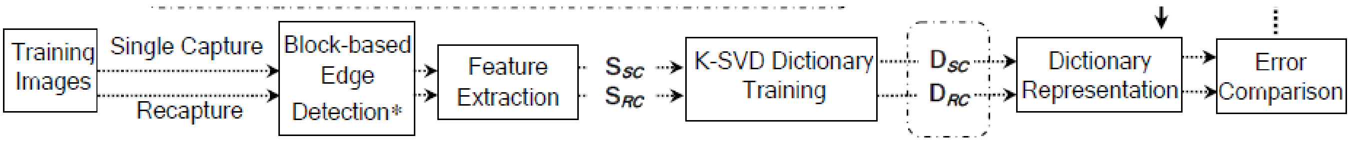

Figure 4: Flow of Recapture detection

Algorithm 2:

Step 1: We trained two dictionaries DSC and DRC using features SSC and SRC extracted from the single captured and recaptured images respectively.

Step 2: Each dictionary is considered to provide an optimal representation of the profiles extracted from edges found in each set of training images, respectively.

Step 3: We now assume that a query image containing edges is available (Algorithm 1).

Step 4: Given the matrix Q ∈ IRW−1×N which represents all line spread profiles extracted from the detected blocks, the decision for recapture detection can be based on the class of dictionary that gives the smallest representation error.

Step 5: We defineX1 andX2 as the coefficient matrices obtained from the composition of query feature matrix Q using the dictionaries DRC and DSC respectively.

Step 6: The query image is classified into a recapture group if Otherwise, the query image is classified to the single capture group.

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

Advantages:
- Method does not require human supervision.
- The does not need presence of sharp edges in query images.

Disadvantages:
- Need to train dictionaries.

4. System Architecture

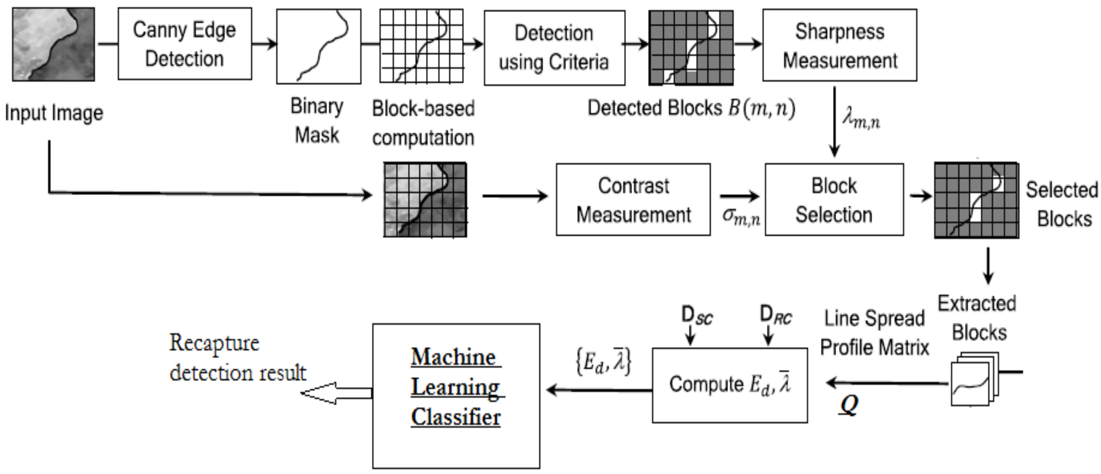

Figure 5: System Architectureof the image classification techniques

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 [19]. 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.

5. Conclusion

In this paper, we study various features which can differentiate original images from recaptured one like aliasing, blurriness, noise, surface gradient etc. Using these features many 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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