Copy-Move Forgery Detection Scheme using SURF Algorithm

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ABSTRACT:

The Image duplication becomes the more common issues in every field. However, the most common type of image forgery is the copy-move process. That’s means copying a part of image and pasting it on the same image, the traditional way to identify copy paste forgery contains two phase, one is segmenting the test image to independent patches before extracting the keypoints and the second phase is finding the matches from the test patches. In this paper, the copy move forgery involves two steps: one is using the SURF algorithm the suspicious pairs is identified by affine transform matrix. The second step is the Expectation-Maximization algorithm is utilized to refine the matrix. The experimental setup in Matlab tool shows that the proposed framework is processed at reduced computational time.

Keywords: Segmentation, SURF algorithm, Key-point extraction.

INTRODUCTION

An Image with copy move fabrication (CMF) contains at minimum two or three districts whose substances are indistinguishable. CMF might be performed by a falsifier pointing either to cover reality or to improve the visual impact of the picture. Ordinary individuals may disregard this malignant operation when the falsifier intentionally conceals the altering follow. So we are in pressing need of a powerful CMF location (CMFD) strategy to consequently call attention to the clone locales in the picture. Also, CMFD is getting to be distinctly a standout amongst the most vital and prevalent computerized measurable systems presently.

In the writing there are essentially two classes of CMFD calculations. One depends on piece savvy division, also, the other on keypoint extraction. They both attempt to distinguish the CMF through portraying the nearby fixes of one picture. The previous first partitions the picture into covering pieces and afterward finds the CMF by searching for the comparable squares. In the creators proposed such a sort of strategy based on DCT portraying the piece, and they likewise diminished the unpredictability of the coordinating
procedure by method for word reference sorting. Since the descriptor of the piece is critical for the calculation, different portrayal strategies like DWT, PCA. Among them Zernike minute might be the best decision in terms of discovery precision and heartiness. Moreover, a few post-preparing strategies were proposed to enhance the CMFD calculations' proficiency.

For instance, in the creators given a technique to the choice of copied pieces, to be specific SATS (Same Affine Transformation Selection). This technique could enhance the heartiness of the recognition calculation against a few assaults like revolution. The inferior of calculations identifies the CMF through watching the keypoints in the picture. Filter and SURF may be the most generally utilized keypoints for CMFD. The creators evaluated the change network between the duplicating source district and sticking target area and in addition distinguishing CMF in the picture. Keeping in mind the end goal to expel the impact of undesirable exceptions, RANSAC was regularly utilized to ensure the strength of the estimation. The creators additionally enhanced the precision of the estimation result got by RANSAC by means of the best quality level calculation. Since the quantity of the keypoints is much littler than that of the pieces separated in a covering way, the keypoint-based calculations require less computational asset than the piece based ones. Perusers are alluded to what's more, for some overview and assessment works.

**PROPOSED SYSTEM:**

SURF approximates the DoG with box filters. Instead of Gaussian averaging the image, squares are used for approximation since the convolution with square is much faster if the integral image is used. Also this can be done in parallel for different scales. The SURF uses a BLOB detector which is based on the Hessian matrix to find the points of interest. For orientation assignment, it uses wavelet responses in both horizontal and vertical directions by applying adequate Gaussian weights. For feature description also SURF uses the wavelet responses. A neighborhood around the key point is selected and divided into subregions and then for each subregion the wavelet responses are taken and represented to get SURF feature descriptor. The sign of Laplacian which is already computed in the detection is used for underlying interest points. The sign of the Laplacian distinguishes bright blobs on dark backgrounds from the reverse case. In case of matching the features are compared only if they have same type of contrast (based on sign) which allows faster matching.

- Image Segmentation
- Keypoint Extraction And Description
- Matching Between Patches
- Iterative Re-Estimation Of The Transform Matrix
Fig 1. Shows the overall flow of the entire system

**Image Segmentation:**

In our proposed CMFD scheme, after segmenting the image, we perform the first stage of affine estimation. During this stage we first extract the keypoints from the whole image and construct a k-d tree. Then the KNN (k-nearest neighbor) search is performed in each region for each keypoint to find a possible correspondence. One region is recorded if it has a certain proportion of keypoints matched with another one. Finally we estimate the affine relationship between the region pairs. The estimated transform matrix is the input to the second stage of matching process, where we iteratively refine the matrix via a probability model based on the EM algorithm. In order to separate the copying source region from the pasting target region, the image should be segmented into small patches, each of which is semantically independent to the others. This job is best done by an expert with much experience of digital forensics. As mentioned above, in order that two CMF regions do not exist in the same patch, we should not coarsely segment the image. In our implementation, each image is empirically segmented into no less than 100 patches and thus, a CMF region may be in two or more patches. In consequence the useful information for CMFD is reduced in each patch. However,
to obtain a convincing detection result we need not a large number of keypoints the clustering object became a vector associated to the candidate transform estimation. It is shown that the new clustering-based CMFD scheme significantly raise the accuracy of localization of CMF regions. We know that an image is seldom forged aimlessly. Hence the copy-move regions should have a certain meaning. In this light, we propose to segment the test image into a number of non-overlapped patches. Then the CMFD can be performed by matching these patches, as long as the pasting target and copying source regions are not in the same patch.

**Keypoint Extraction And Description:**

In our implementation, to help us to detect and describe the keypoints. There are many kinds of keypoint detection and description methods. The common co-variant keypoint detection and description algorithms, such as difference of Gaussian (DoG), Harris-affine and Hessian-affine can provide similar detection performance. In our implementation we just employ the default setting of vlFeat for keypoints detection and description, namely SIFT. We describe here two related methods which detect interest points in scale-space, and then determine an elliptical region for each point. Interest points are either detected with the Harris detector or with a detector based on the Hessian matrix. In both cases scale-selection is based on the Laplacian, and the shape of the elliptical region is determined with the second moment matrix of the intensity gradient. The second moment matrix, also called the autocorrelation matrix, is often used for feature detection or for describing local image structures. Here it is used both in the Harris detector and the elliptical shape estimation. This matrix describes the gradient distribution in a local neighbourhood of a point:

\[
M = \mu(x, \sigma_I, \sigma_D) = \begin{bmatrix}
\mu_{11} & \mu_{12} \\
\mu_{21} & \mu_{22}
\end{bmatrix} = \sigma_D^2 g(\sigma_I) * \begin{bmatrix}
I_x^2(x, \sigma_D) & I_xI_y(x, \sigma_D) \\
I_xI_y(x, \sigma_D) & I_y^2(x, \sigma_D)
\end{bmatrix}
\]

The local images derivatives are computed with Gaussian kernels of scale \(\sigma_D\) (differentiation scale). The derivatives are then averaged in the neighborhood of the point by smoothing with a Gaussian window of scale \(\sigma_I\) (integration scale). The eigenvalues of this matrix represent two
principal signal changes in a neighborhood of the point. This property enables the extraction of points, for which both curvatures are significant, that is the signal change is significant in orthogonal directions. Such points are stable in arbitrary lighting conditions and are representative of an image.

EXPERIMENTAL RESULTS:

Fig. 2 Represent the input image taken for further processing
Fig. 3 Represent the segmentation of the input image

Fig. 4 Represent the keypoint detection of the input image

CONCLUSION

The copy move forgery is the major issue in every field. This work is used to find whether the image is forged one or not. This work deals with the detection of copymove attack. The paper detects the
multiple copies of same region and multiple copies of different region of copy-move forgery. The features can be extracted by using keypoint method called SURF. Then the Expectation-Maximization algorithm is utilized to refine the matrix. This proposed work took less time the entire computational process such as segmenting, keypoint extraction. This work does not identify other types of image tampering techniques such as enhancing and splicing attack and it identifies only the copy move forgery. The future work is to identify such attacks.

**REFERENCE**


